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(54) **PREDICTIVE MAP GENERATION AND CONTROL SYSTEM FOR AN AGRICULTURAL WORK MACHINE**

(71) Applicant: **Deere & Company**, Moline, IL (US)

(72) Inventors: **Nathan R Vandike**, Geneseo, IL (US); **Bhanu Kiran Reddy Palla**, Bettendorf, IA (US); **Duane M. Bomleny**, Geneseo, IL (US); **Colin D. Engel**, Bettendorf, IA (US); **Stephen R. Corban**, Geneseo, IL (US)

(73) Assignee: **Deere & Company**, Moline, IL (US)

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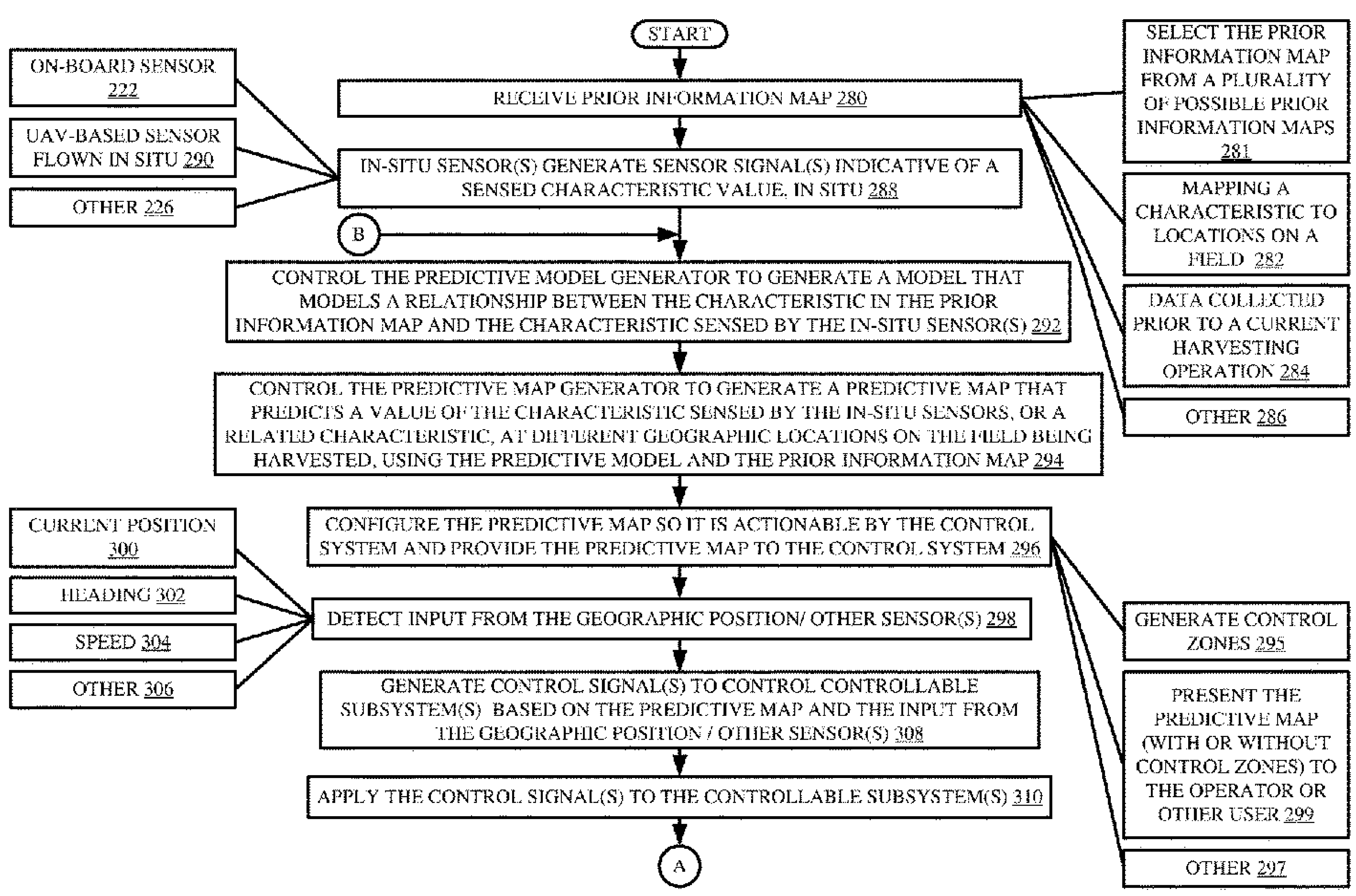
Primary Examiner — Jess Whittington
Assistant Examiner — Terry C Buse
(74) *Attorney, Agent, or Firm* — Kelly, Holt & Christenson; Joseph R. Kelly

(57) **ABSTRACT**

One or more information maps are obtained by an agricultural work machine. The one or more information maps map one or more agricultural characteristic values at different geographic locations of a field. An in-situ sensor on the agricultural work machine senses an agricultural characteristic as the agricultural work machine moves through the field. A predictive map generator generates a predictive map that predicts a predictive agricultural characteristic at different locations in the field based on a relationship between the values in the one or more information maps and the agricultural characteristic sensed by the in-situ sensor. The predictive map can be output and used in automated machine control.

18 Claims, 21 Drawing Sheets



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See application file for complete search history.

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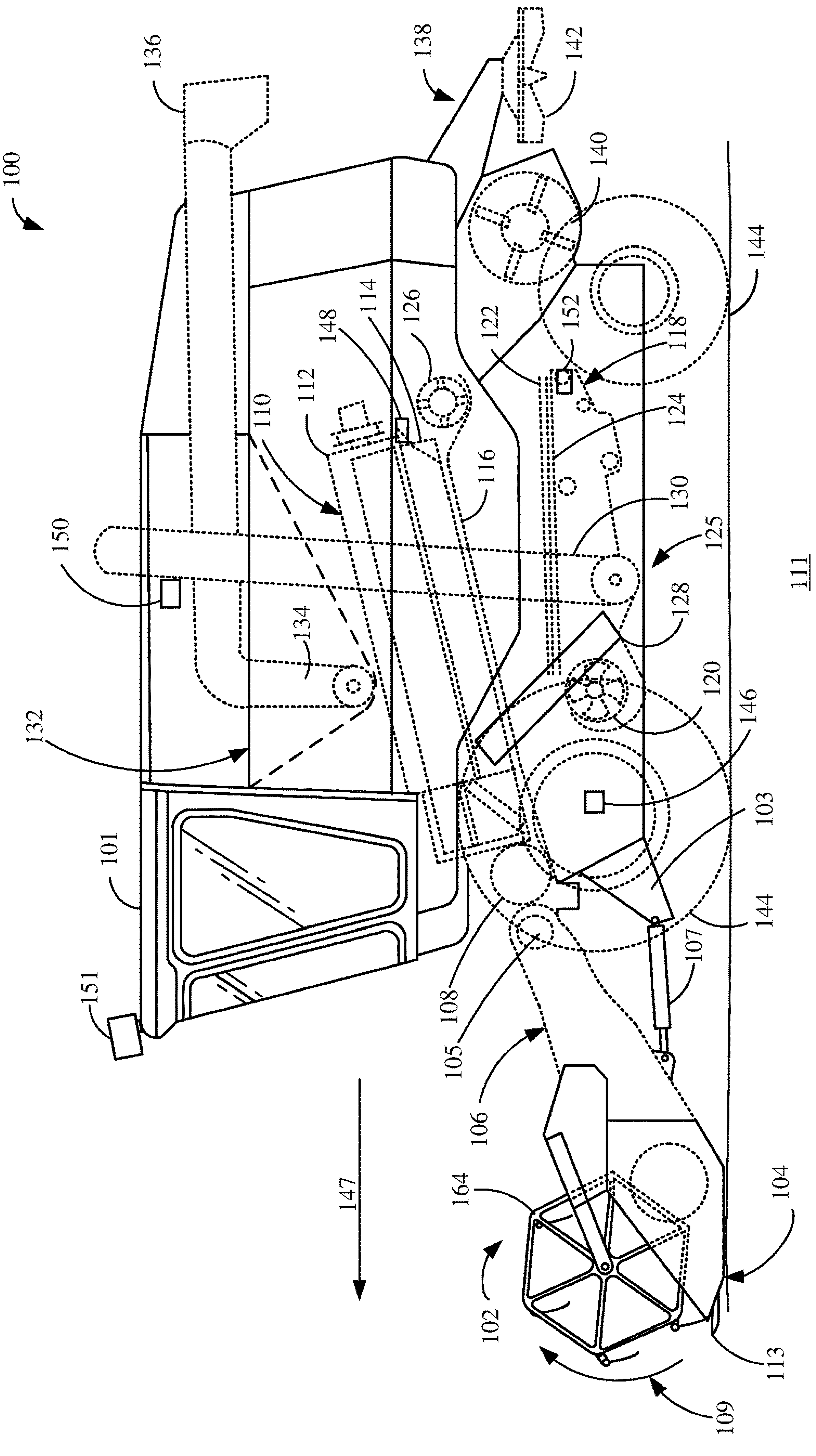
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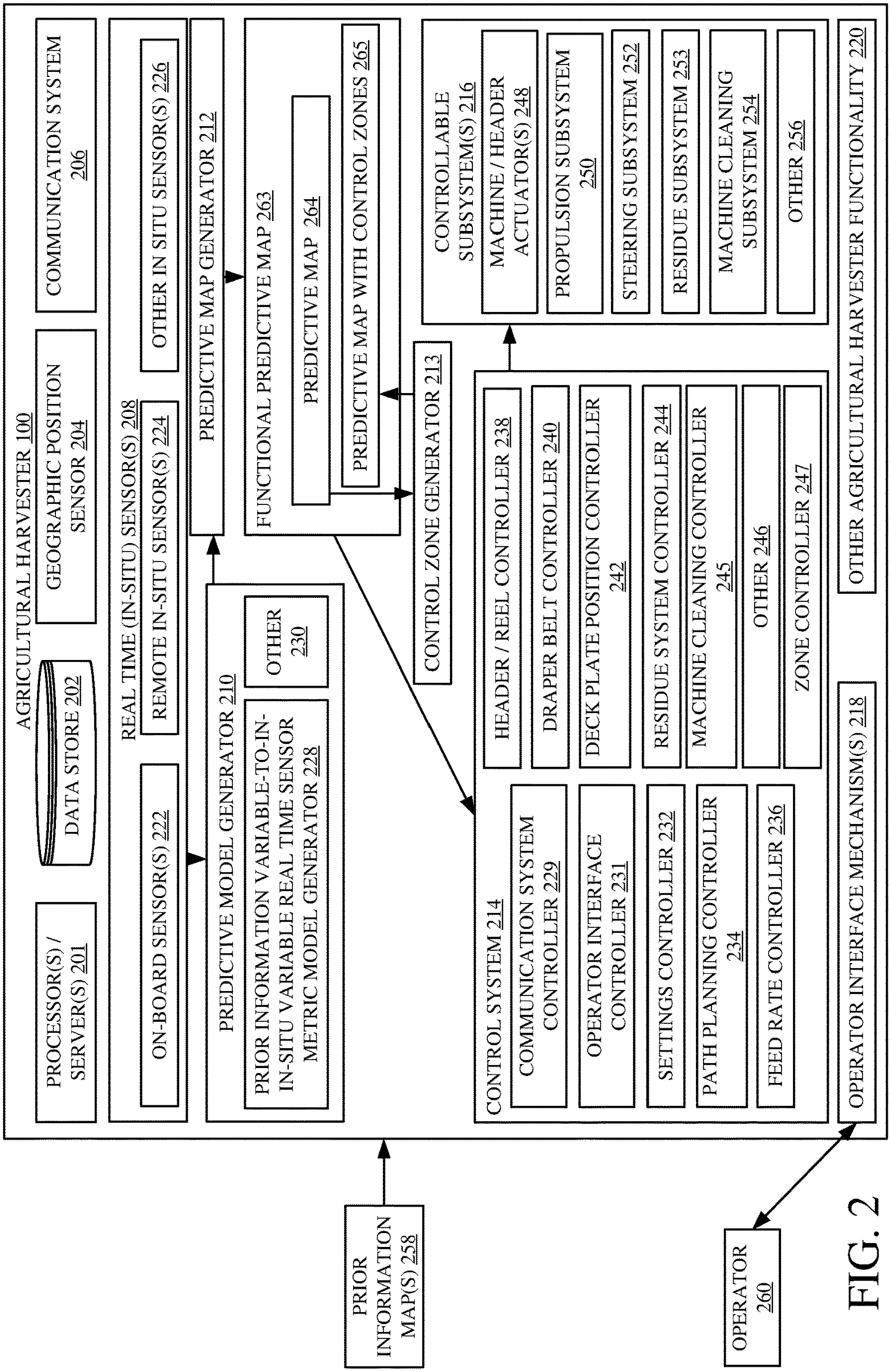
FIG. 1


AGRICULTURAL HARVESTER 100
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GEOGRAPHIC POSITION SENSOR 204
COMMUNICATION SYSTEM 206
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HEADER / REEL CONTROLLER 238
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RESIDUE SYSTEM CONTROLLER 244
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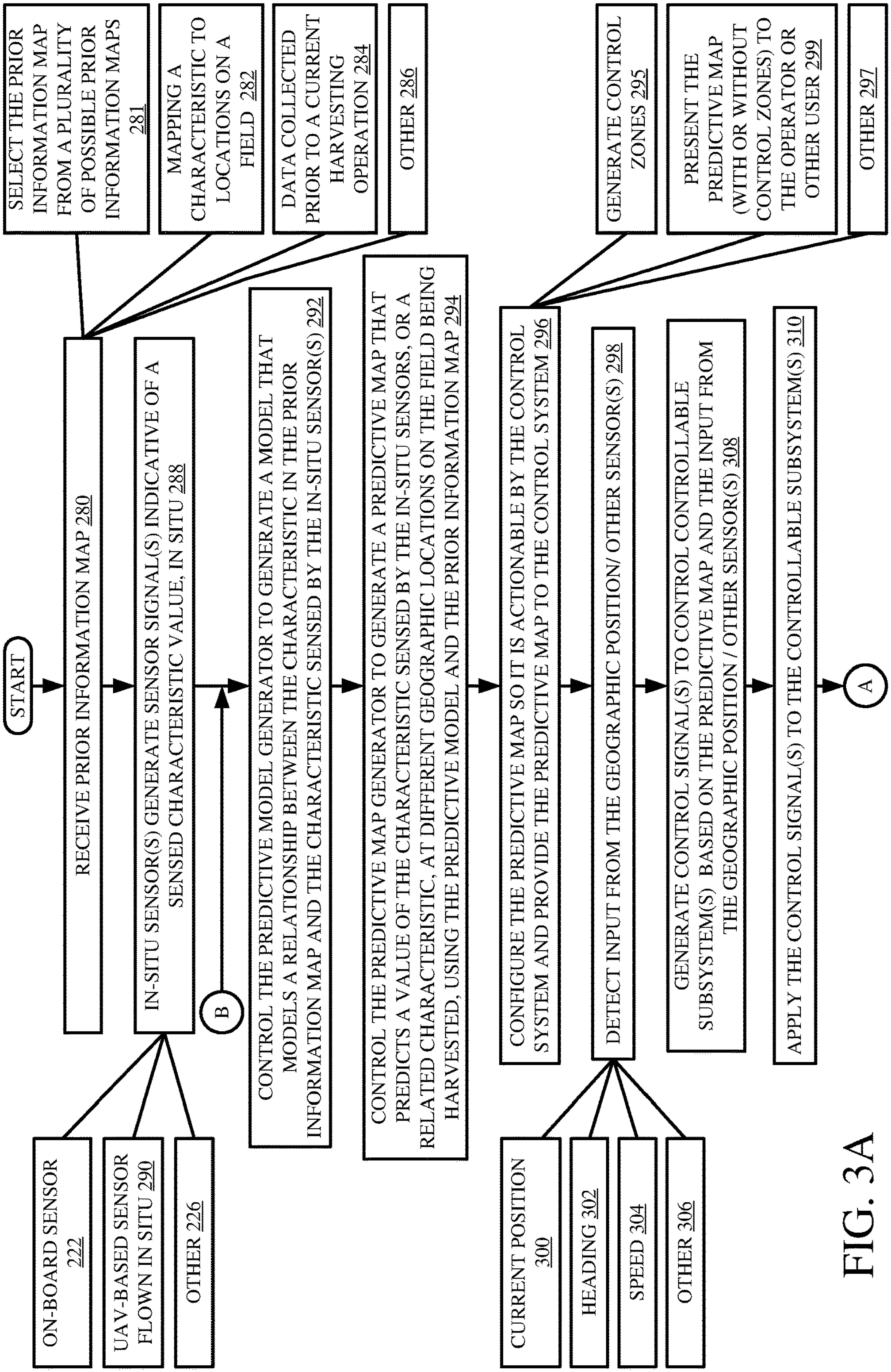
FIG. 2


START
RECEIVE PRIOR INFORMATION MAP 280
SELECT THE PRIOR INFORMATION MAP FROM A PLURALITY OF POSSIBLE PRIOR INFORMATION MAPS 281
MAPPING A CHARACTERISTIC TO LOCATIONS ON A FIELD 282
DATA COLLECTED PRIOR TO A CURRENT HARVESTING OPERATION 284
OTHER 286
IN-SITU SENSOR(S) GENERATE SENSOR SIGNAL(S) INDICATIVE OF A SENSED CHARACTERISTIC VALUE, IN SITU 288
ON-BOARD SENSOR 222
UAV-BASED SENSOR FLOWN IN SITU 290
OTHER 226
B
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CONTROL THE PREDICTIVE MAP GENERATOR TO GENERATE A PREDICTIVE MAP THAT PREDICTS A VALUE OF THE CHARACTERISTIC SENSED BY THE IN-SITU SENSORS, OR A RELATED CHARACTERISTIC, AT DIFFERENT GEOGRAPHIC LOCATIONS ON THE FIELD BEING HARVESTED, USING THE PREDICTIVE MODEL AND THE PRIOR INFORMATION MAP 294
CONFIGURE THE PREDICTIVE MAP SO IT IS ACTIONABLE BY THE CONTROL SYSTEM AND PROVIDE THE PREDICTIVE MAP TO THE CONTROL SYSTEM 296
GENERATE CONTROL ZONES 295
PRESENT THE PREDICTIVE MAP (WITH OR WITHOUT CONTROL ZONES) TO THE OPERATOR OR OTHER USER 299
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DETECT INPUT FROM THE GEOGRAPHIC POSITION/ OTHER SENSOR(S) 298
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OTHER 306
GENERATE CONTROL SIGNAL(S) TO CONTROL CONTROLLABLE SUBSYSTEM(S) BASED ON THE PREDICTIVE MAP AND THE INPUT FROM THE GEOGRAPHIC POSITION / OTHER SENSOR(S) 308
APPLY THE CONTROL SIGNAL(S) TO THE CONTROLLABLE SUBSYSTEM(S) 310
A

FIG. 3A

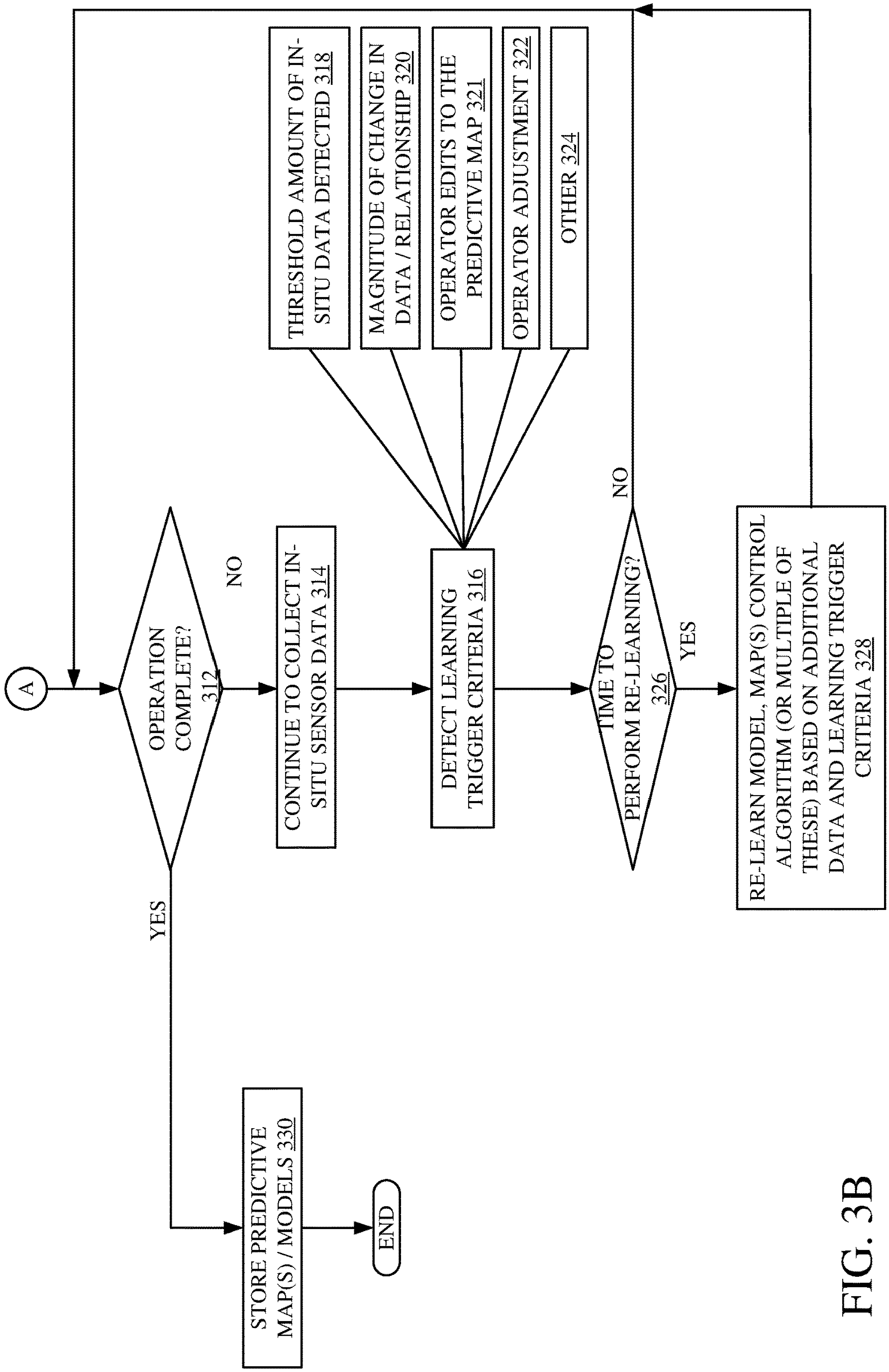
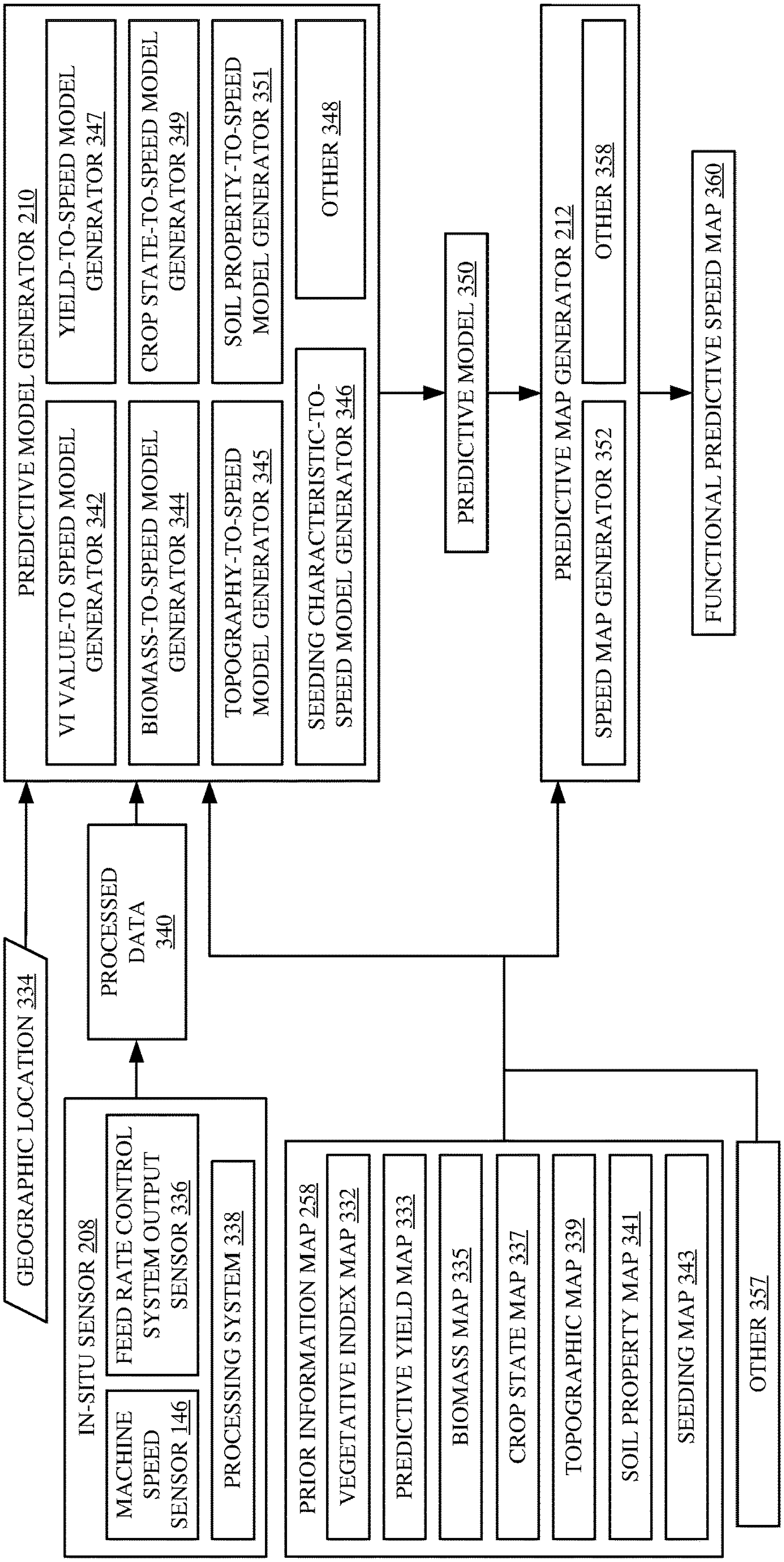

A
OPERATION COMPLETE? 312
NO
YES
CONTINUE TO COLLECT IN-SITU SENSOR DATA 314
DETECT LEARNING TRIGGER CRITERIA 316
THRESHOLD AMOUNT OF IN-SITU DATA DETECTED 318
MAGNITUDE OF CHANGE IN DATA / RELATIONSHIP 320
OPERATOR EDITS TO THE PREDICTIVE MAP 321
OPERATOR ADJUSTMENT 322
OTHER 324
TIME TO PERFORM RE-LEARNING? 326
NO
YES
RE-LEARN MODEL, MAP(S) CONTROL ALGORITHM (OR MULTIPLE OF THESE) BASED ON ADDITIONAL DATA AND LEARNING TRIGGER CRITERIA 328
STORE PREDICTIVE MAP(S) / MODELS 330
END

FIG. 3B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VI VALUE-TO-SPEED MODEL GENERATOR 342
YIELD-TO-SPEED MODEL GENERATOR 347
BIOMASS-TO-SPEED MODEL GENERATOR 344
CROP STATE-TO-SPEED MODEL GENERATOR 349
TOPOGRAPHY-TO-SPEED MODEL GENERATOR 345
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PROCESSING SYSTEM 338
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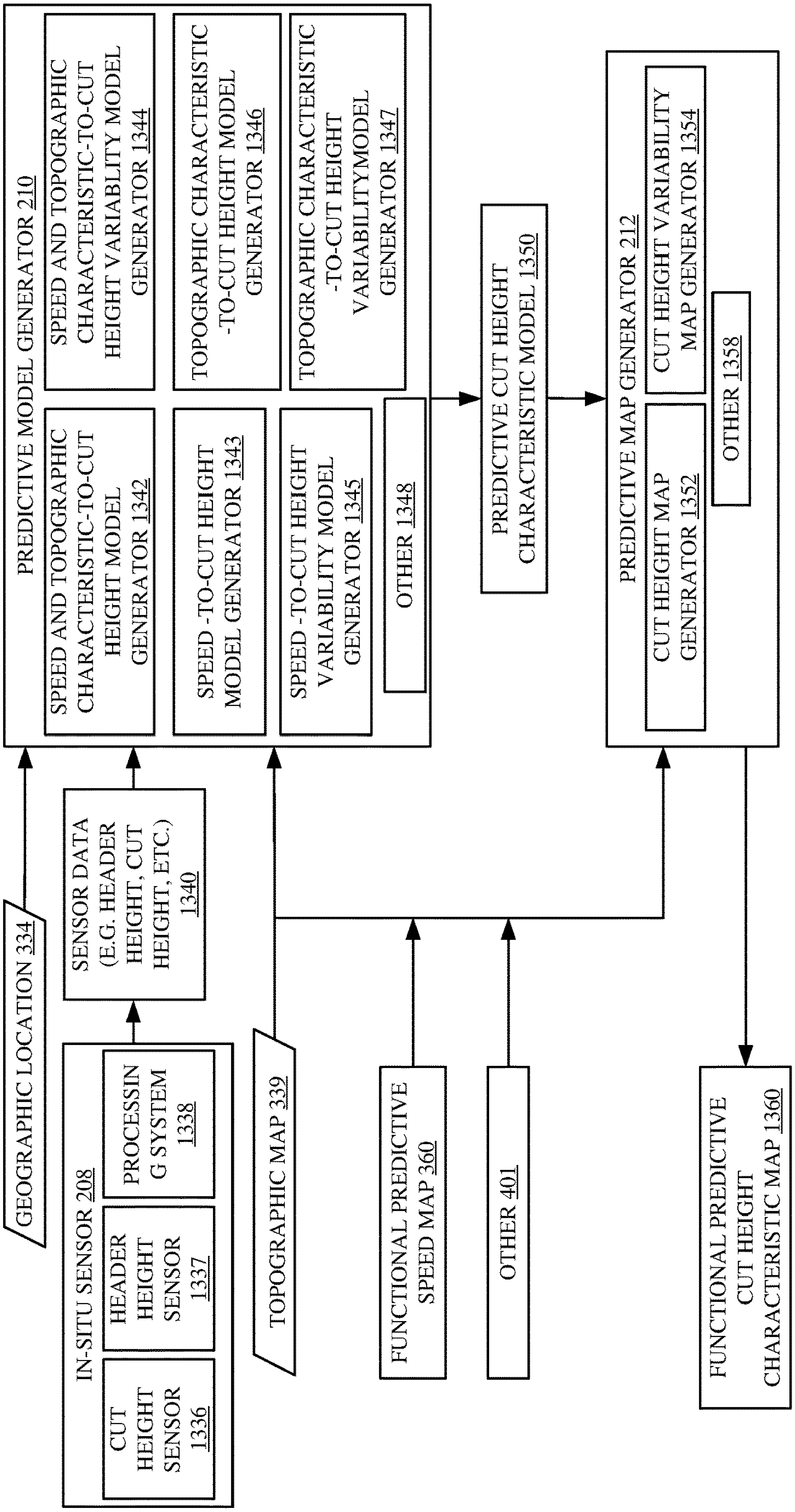
VEGETATIVE INDEX MAP 332
PREDICTIVE YIELD MAP 333
BIOMASS MAP 335
CROP STATE MAP 337
TOPOGRAPHIC MAP 339
SOIL PROPERTY MAP 341
SEEDING MAP 343
OTHER 357

FIG. 4A


GEOGRAPHIC LOCATION 334
IN-SITU SENSOR 208
CUT HEIGHT SENSOR 1336
HEADER HEIGHT SENSOR 1337
PROCESSING SYSTEM 1338
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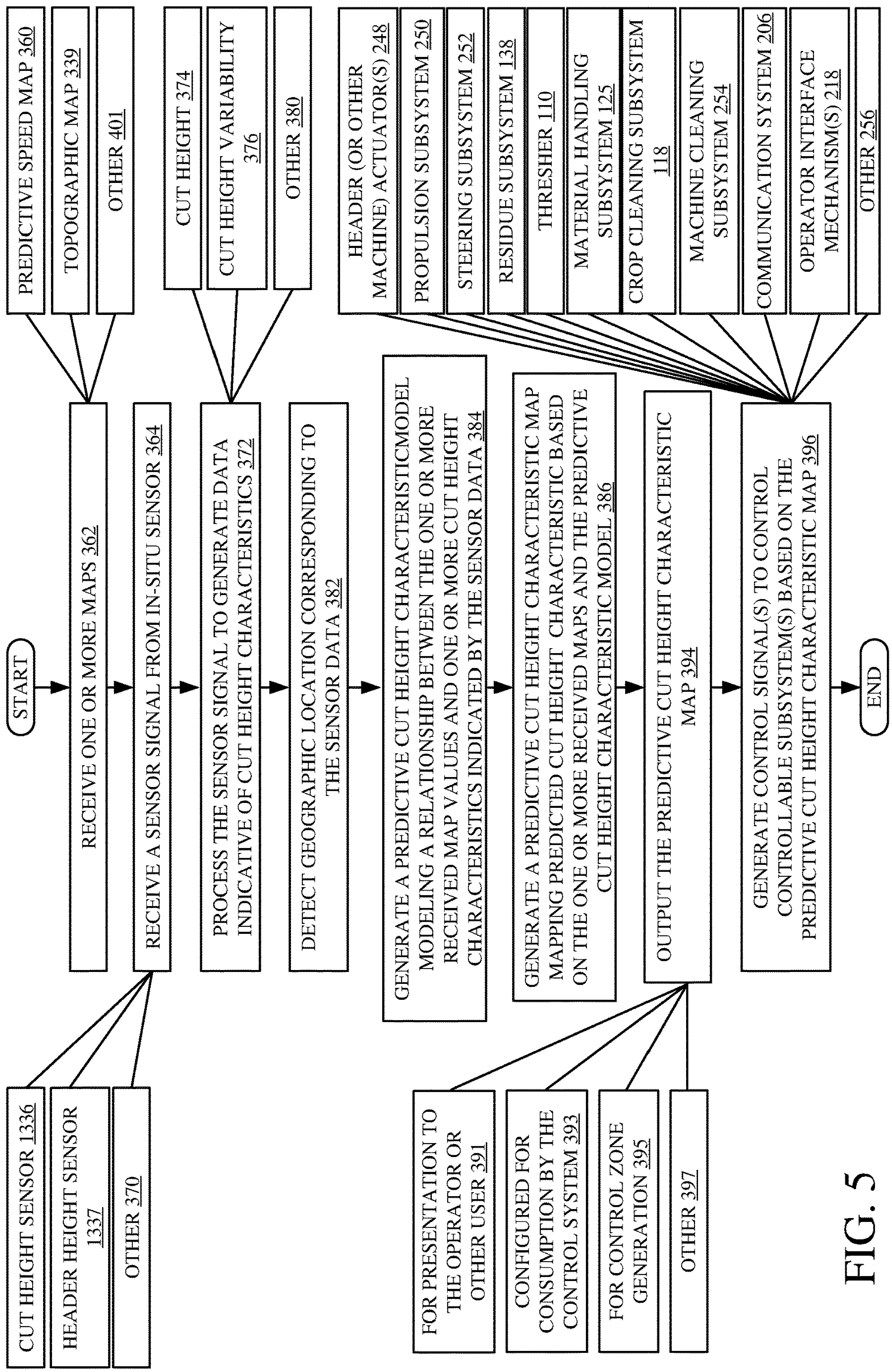
SPEED AND TOPOGRAPHIC CHARACTERISTIC-TO-CUT HEIGHT VARIABLITY MODEL GENERATOR 1344
SPEED -TO-CUT HEIGHT MODEL GENERATOR 1343
TOPOGRAPHIC CHARACTERISTIC -TO-CUT HEIGHT MODEL GENERATOR 1346
SPEED -TO-CUT HEIGHT VARIABILITY MODEL GENERATOR 1345
TOPOGRAPHIC CHARACTERISTIC -TO-CUT HEIGHT VARIABILITYMODEL GENERATOR 1347
OTHER 1348
PREDICTIVE CUT HEIGHT CHARACTERISTIC MODEL 1350
PREDICTIVE MAP GENERATOR 212
CUT HEIGHT MAP GENERATOR 1352
CUT HEIGHT VARIABILITY MAP GENERATOR 1354
OTHER 1358
FUNCTIONAL PREDICTIVE CUT HEIGHT CHARACTERISTIC MAP 1360

FIG. 4B


START
RECEIVE ONE OR MORE MAPS 362
PREDICTIVE SPEED MAP 360
TOPOGRAPHIC MAP 339
OTHER 401
RECEIVE A SENSOR SIGNAL FROM IN-SITU SENSOR 364
CUT HEIGHT SENSOR 1336
HEADER HEIGHT SENSOR 1337
OTHER 370
PROCESS THE SENSOR SIGNAL TO GENERATE DATA INDICATIVE OF CUT HEIGHT CHARACTERISTICS 372
CUT HEIGHT 374
CUT HEIGHT VARIABILITY 376
OTHER 380
DETECT GEOGRAPHIC LOCATION CORRESPONDING TO THE SENSOR DATA 382
GENERATE A PREDICTIVE CUT HEIGHT CHARACTERISTICMODEL MODELING A RELATIONSHIP BETWEEN THE ONE OR MORE RECEIVED MAP VALUES AND ONE OR MORE CUT HEIGHT CHARACTERISTICS INDICATED BY THE SENSOR DATA 384
GENERATE A PREDICTIVE CUT HEIGHT CHARACTERISTIC MAP MAPPING PREDICTED CUT HEIGHT CHARACTERISTIC BASED ON THE ONE OR MORE RECEIVED MAPS AND THE PREDICTIVE CUT HEIGHT CHARACTERISTIC MODEL 386
OUTPUT THE PREDICTIVE CUT HEIGHT CHARACTERISTIC MAP 394
FOR PRESENTATION TO THE OPERATOR OR OTHER USER 391
CONFIGURED FOR CONSUMPTION BY THE CONTROL SYSTEM 393
FOR CONTROL ZONE GENERATION 395
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GENERATE CONTROL SIGNAL(S) TO CONTROL CONTROLLABLE SUBSYSTEM(S) BASED ON THE PREDICTIVE CUT HEIGHT CHARACTERISTIC MAP 396
HEADER (OR OTHER MACHINE) ACTUATOR(S) 248
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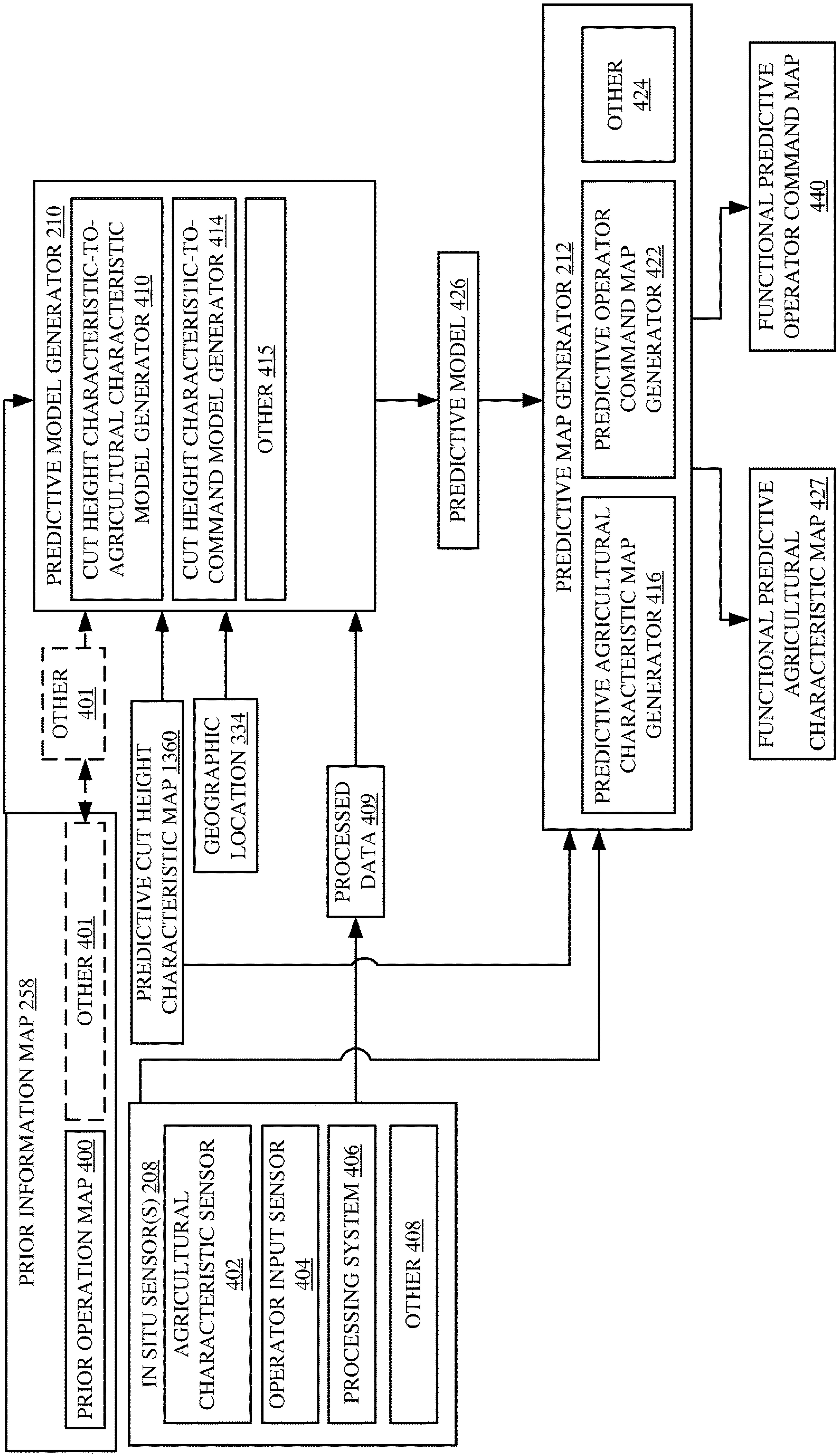
STEERING SUBSYSTEM 252
RESIDUE SUBSYSTEM 138
THRESHER 110
MATERIAL HANDLING SUBSYSTEM 125
CROP CLEANING SUBSYSTEM 118
MACHINE CLEANING SUBSYSTEM 254
COMMUNICATION SYSTEM 206
OPERATOR INTERFACE MECHANISM(S) 218
OTHER 256
END

FIG. 5


PRIOR INFORMATION MAP 258
PRIOR OPERATION MAP 400
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CUT HEIGHT CHARACTERISTIC-TO-COMMAND MODEL GENERATOR 414
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PREDICTIVE AGRICULTURAL CHARACTERISTIC MAP GENERATOR 416
PREDICTIVE OPERATOR COMMAND MAP GENERATOR 422
OTHER 424
FUNCTIONAL PREDICTIVE AGRICULTURAL CHARACTERISTIC MAP 427
FUNCTIONAL PREDICTIVE OPERATOR COMMAND MAP 440

FIG. 6A

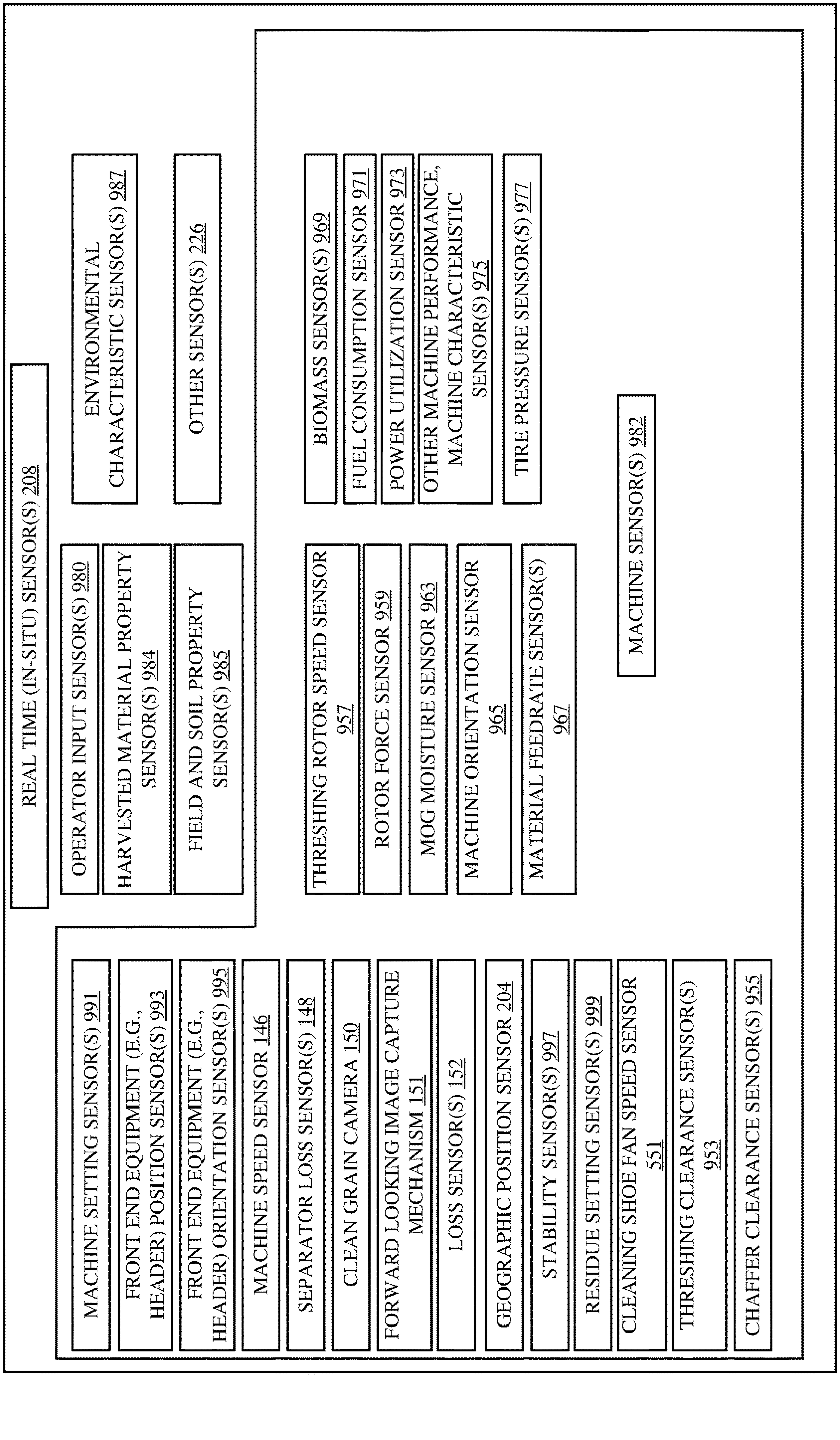
REAL TIME (IN-SITU) SENSOR(S) 208
ENVIRONMENTAL CHARACTERISTIC SENSOR(S) 987
OTHER SENSOR(S) 226
OPERATOR INPUT SENSOR(S) 980
HARVESTED MATERIAL PROPERTY SENSOR(S) 984
FIELD AND SOIL PROPERTY SENSOR(S) 985
BIOMASS SENSOR(S) 969
FUEL CONSUMPTION SENSOR 971
POWER UTILIZATION SENSOR 973
OTHER MACHINE PERFORMANCE, MACHINE CHARACTERISTIC SENSOR(S) 975
TIRE PRESSURE SENSOR(S) 977
THRESHING ROTOR SPEED SENSOR 957
ROTOR FORCE SENSOR 959
MOG MOISTURE SENSOR 963
MACHINE ORIENTATION SENSOR 965
MATERIAL FEEDRATE SENSOR(S) 967
MACHINE SENSOR(S) 982
MACHINE SETTING SENSOR(S) 991
FRONT END EQUIPMENT (E.G., HEADER) POSITION SENSOR(S) 993
FRONT END EQUIPMENT (E.G., HEADER) ORIENTATION SENSOR(S) 995
MACHINE SPEED SENSOR 146
SEPARATOR LOSS SENSOR(S) 148
CLEAN GRAIN CAMERA 150
FORWARD LOOKING IMAGE CAPTURE MECHANISM 151
LOSS SENSOR(S) 152
GEOGRAPHIC POSITION SENSOR 204
STABILITY SENSOR(S) 997
RESIDUE SETTING SENSOR(S) 999
CLEANING SHOE FAN SPEED SENSOR 551
THRESHING CLEARANCE SENSOR(S) 953
CHAFFER CLEARANCE SENSOR(S) 955

FIG. 6B

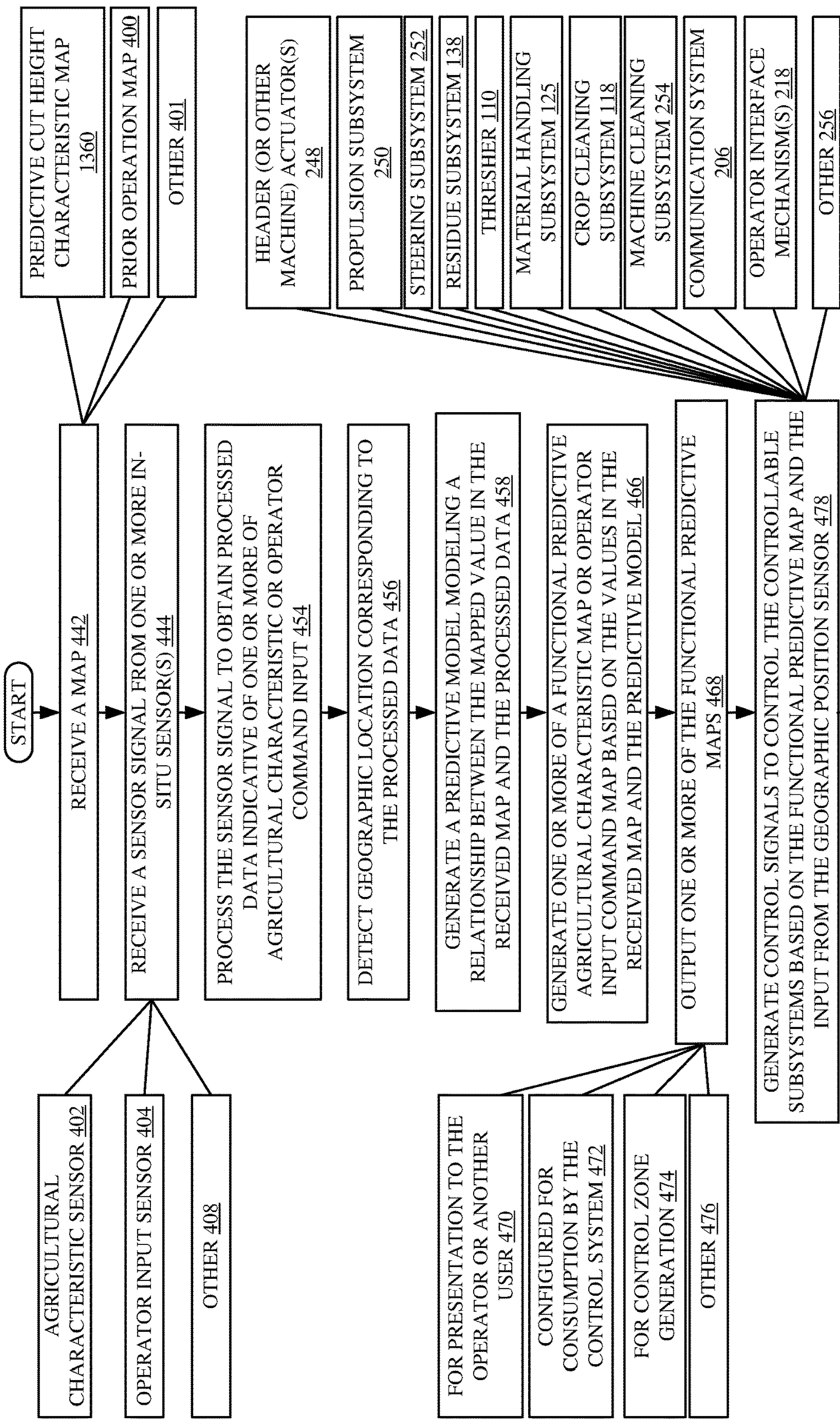
START
RECEIVE A MAP 442
PREDICTIVE CUT HEIGHT CHARACTERISTIC MAP 1360
PRIOR OPERATION MAP 400
OTHER 401
RECEIVE A SENSOR SIGNAL FROM ONE OR MORE IN-SITU SENSOR(S) 444
AGRICULTURAL CHARACTERISTIC SENSOR 402
OPERATOR INPUT SENSOR 404
OTHER 408
PROCESS THE SENSOR SIGNAL TO OBTAIN PROCESSED DATA INDICATIVE OF ONE OR MORE OF AGRICULTURAL CHARACTERISTIC OR OPERATOR COMMAND INPUT 454
DETECT GEOGRAPHIC LOCATION CORRESPONDING TO THE PROCESSED DATA 456
GENERATE A PREDICTIVE MODEL MODELING A RELATIONSHIP BETWEEN THE MAPPED VALUE IN THE RECEIVED MAP AND THE PROCESSED DATA 458
GENERATE ONE OR MORE OF A FUNCTIONAL PREDICTIVE AGRICULTURAL CHARACTERISTIC MAP OR OPERATOR INPUT COMMAND MAP BASED ON THE VALUES IN THE RECEIVED MAP AND THE PREDICTIVE MODEL 466
OUTPUT ONE OR MORE OF THE FUNCTIONAL PREDICTIVE MAPS 468
FOR PRESENTATION TO THE OPERATOR OR ANOTHER USER 470
CONFIGURED FOR CONSUMPTION BY THE CONTROL SYSTEM 472
FOR CONTROL ZONE GENERATION 474
OTHER 476
GENERATE CONTROL SIGNALS TO CONTROL THE CONTROLLABLE SUBSYSTEMS BASED ON THE FUNCTIONAL PREDICTIVE MAP AND THE INPUT FROM THE GEOGRAPHIC POSITION SENSOR 478
HEADER (OR OTHER MACHINE) ACTUATOR(S) 248
PROPULSION SUBSYSTEM 250
STEERING SUBSYSTEM 252
RESIDUE SUBSYSTEM 138
THRESHER 110
MATERIAL HANDLING SUBSYSTEM 125
CROP CLEANING SUBSYSTEM 118
MACHINE CLEANING SUBSYSTEM 254
COMMUNICATION SYSTEM 206
OPERATOR INTERFACE MECHANISM(S) 218
OTHER 256
END

FIG. 7

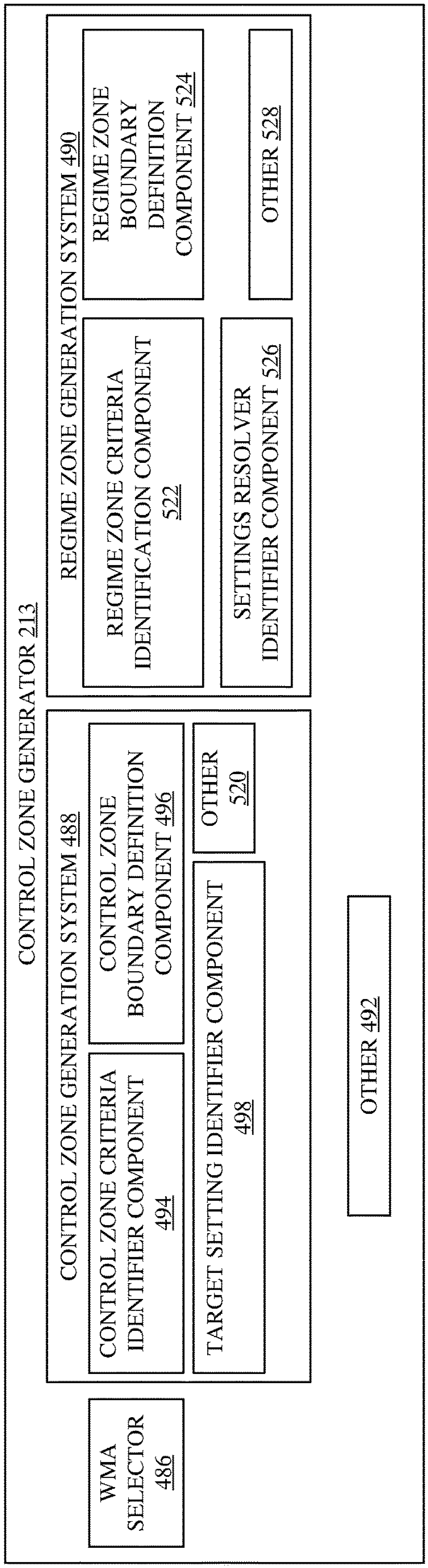
CONTROL ZONE GENERATOR 213
WMA SELECTOR 486
CONTROL ZONE GENERATION SYSTEM 488
CONTROL ZONE CRITERIA IDENTIFIER COMPONENT 494
CONTROL ZONE BOUNDARY DEFINITION COMPONENT 496
TARGET SETTING IDENTIFIER COMPONENT 498
OTHER 520
REGIME ZONE GENERATION SYSTEM 490
REGIME ZONE CRITERIA IDENTIFICATION COMPONENT 522
REGIME ZONE BOUNDARY DEFINITION COMPONENT 524
SETTINGS RESOLVER IDENTIFIER COMPONENT 526
OTHER 528
OTHER 492

FIG. 8

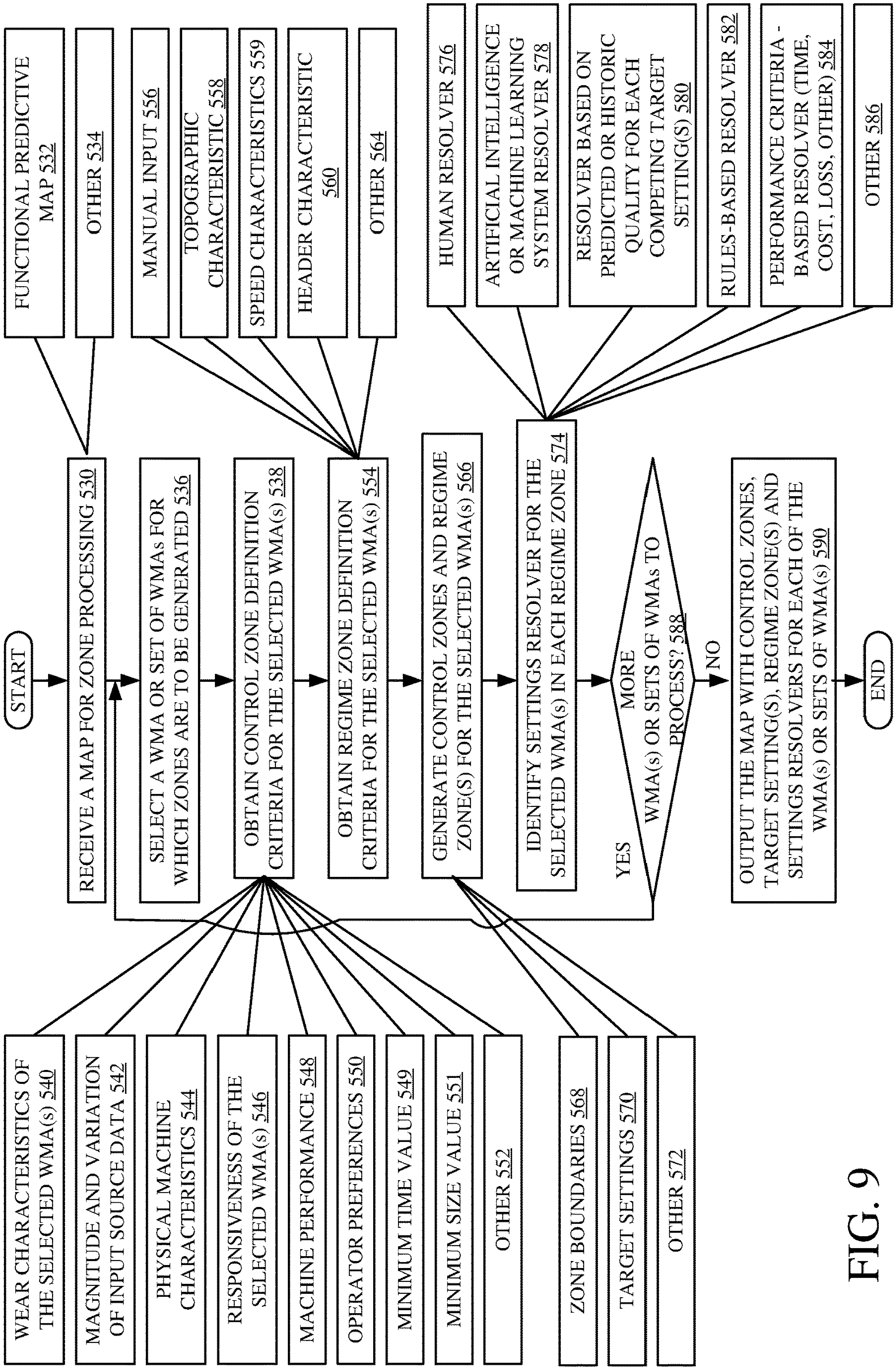
START
RECEIVE A MAP FOR ZONE PROCESSING 530
FUNCTIONAL PREDICTIVE MAP 532
OTHER 534
SELECT A WMA OR SET OF WMAs FOR WHICH ZONES ARE TO BE GENERATED 536
OBTAIN CONTROL ZONE DEFINITION CRITERIA FOR THE SELECTED WMA(s) 538
WEAR CHARACTERISTICS OF THE SELECTED WMA(s) 540
MAGNITUDE AND VARIATION OF INPUT SOURCE DATA 542
PHYSICAL MACHINE CHARACTERISTICS 544
RESPONSIVENESS OF THE SELECTED WMA(s) 546
MACHINE PERFORMANCE 548
OPERATOR PREFERENCES 550
MINIMUM TIME VALUE 549
MINIMUM SIZE VALUE 551
OTHER 552
OBTAIN REGIME ZONE DEFINITION CRITERIA FOR THE SELECTED WMA(s) 554
MANUAL INPUT 556
TOPOGRAPHIC CHARACTERISTIC 558
SPEED CHARACTERISTICS 559
HEADER CHARACTERISTIC 560
OTHER 564
GENERATE CONTROL ZONES AND REGIME ZONE(S) FOR THE SELECTED WMA(s) 566
ZONE BOUNDARIES 568
TARGET SETTINGS 570
OTHER 572
IDENTIFY SETTINGS RESOLVER FOR THE SELECTED WMA(s) IN EACH REGIME ZONE 574
HUMAN RESOLVER 576
ARTIFICIAL INTELLIGENCE OR MACHINE LEARNING SYSTEM RESOLVER 578
RESOLVER BASED ON PREDICTED OR HISTORIC QUALITY FOR EACH COMPETING TARGET SETTING(S) 580
RULES-BASED RESOLVER 582
PERFORMANCE CRITERIA - BASED RESOLVER (TIME, COST, LOSS, OTHER) 584
OTHER 586
MORE WMA(s) OR SETS OF WMAs TO PROCESS? 588
YES
NO
OUTPUT THE MAP WITH CONTROL ZONES, TARGET SETTING(S), REGIME ZONE(S) AND SETTINGS RESOLVERS FOR EACH OF THE WMA(s) OR SETS OF WMA(s) 590
END

FIG. 9

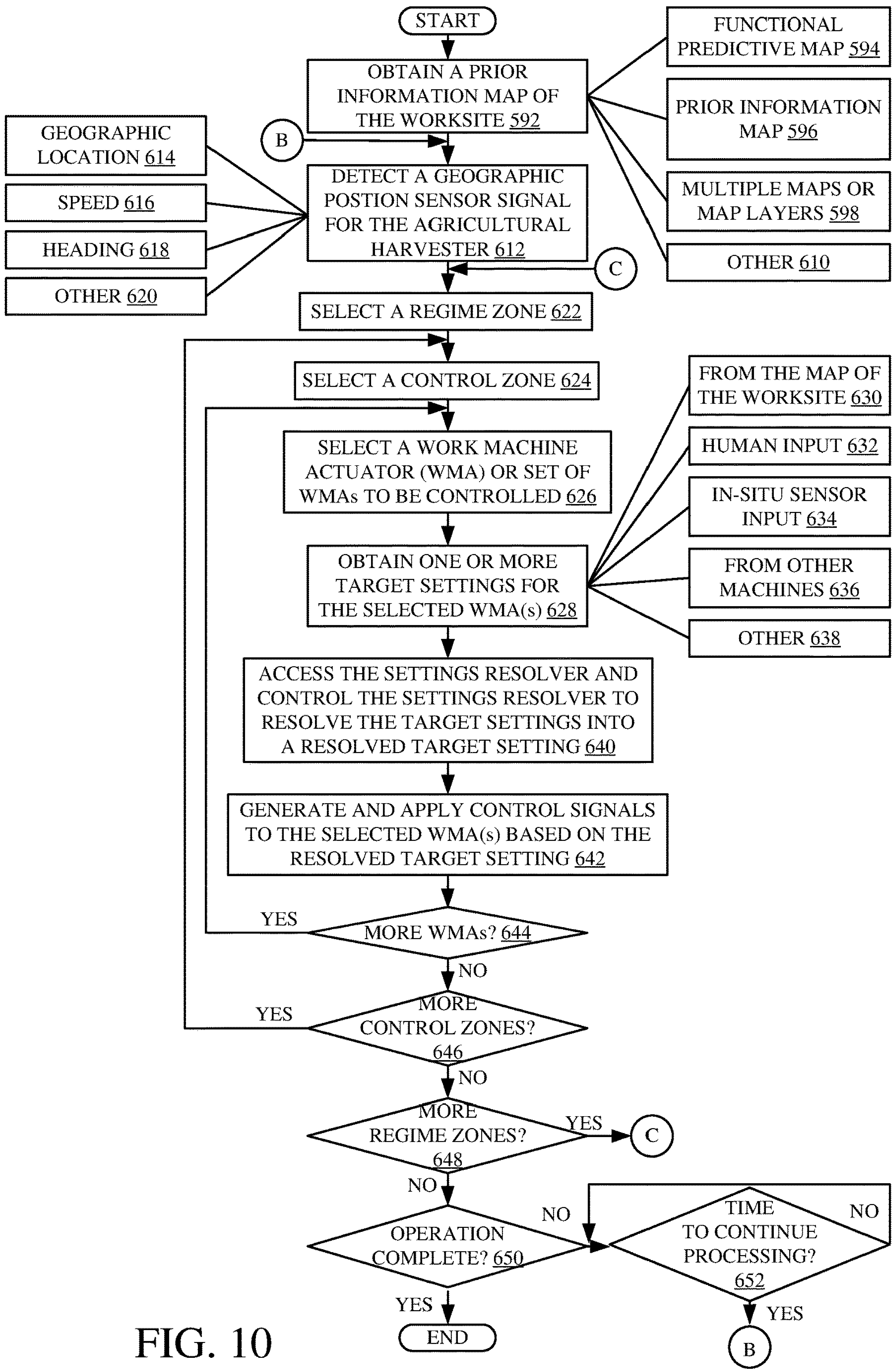
START
OBTAIN A PRIOR INFORMATION MAP OF THE WORKSITE 592
FUNCTIONAL PREDICTIVE MAP 594
PRIOR INFORMATION MAP 596
MULTIPLE MAPS OR MAP LAYERS 598
OTHER 610
B
GEOGRAPHIC LOCATION 614
SPEED 616
HEADING 618
OTHER 620
DETECT A GEOGRAPHIC POSTION SENSOR SIGNAL FOR THE AGRICULTURAL HARVESTER 612
C
SELECT A REGIME ZONE 622
SELECT A CONTROL ZONE 624
SELECT A WORK MACHINE ACTUATOR (WMA) OR SET OF WMAs TO BE CONTROLLED 626
OBTAIN ONE OR MORE TARGET SETTINGS FOR THE SELECTED WMA(s) 628
FROM THE MAP OF THE WORKSITE 630
HUMAN INPUT 632
IN-SITU SENSOR INPUT 634
FROM OTHER MACHINES 636
OTHER 638
ACCESS THE SETTINGS RESOLVER AND CONTROL THE SETTINGS RESOLVER TO RESOLVE THE TARGET SETTINGS INTO A RESOLVED TARGET SETTING 640
GENERATE AND APPLY CONTROL SIGNALS TO THE SELECTED WMA(s) BASED ON THE RESOLVED TARGET SETTING 642
YES
MORE WMAs? 644
NO
YES
MORE CONTROL ZONES? 646
NO
MORE REGIME ZONES? 648
YES
C
NO
OPERATION COMPLETE? 650
NO
TIME TO CONTINUE PROCESSING? 652
NO
YES
B
YES
END

FIG. 10

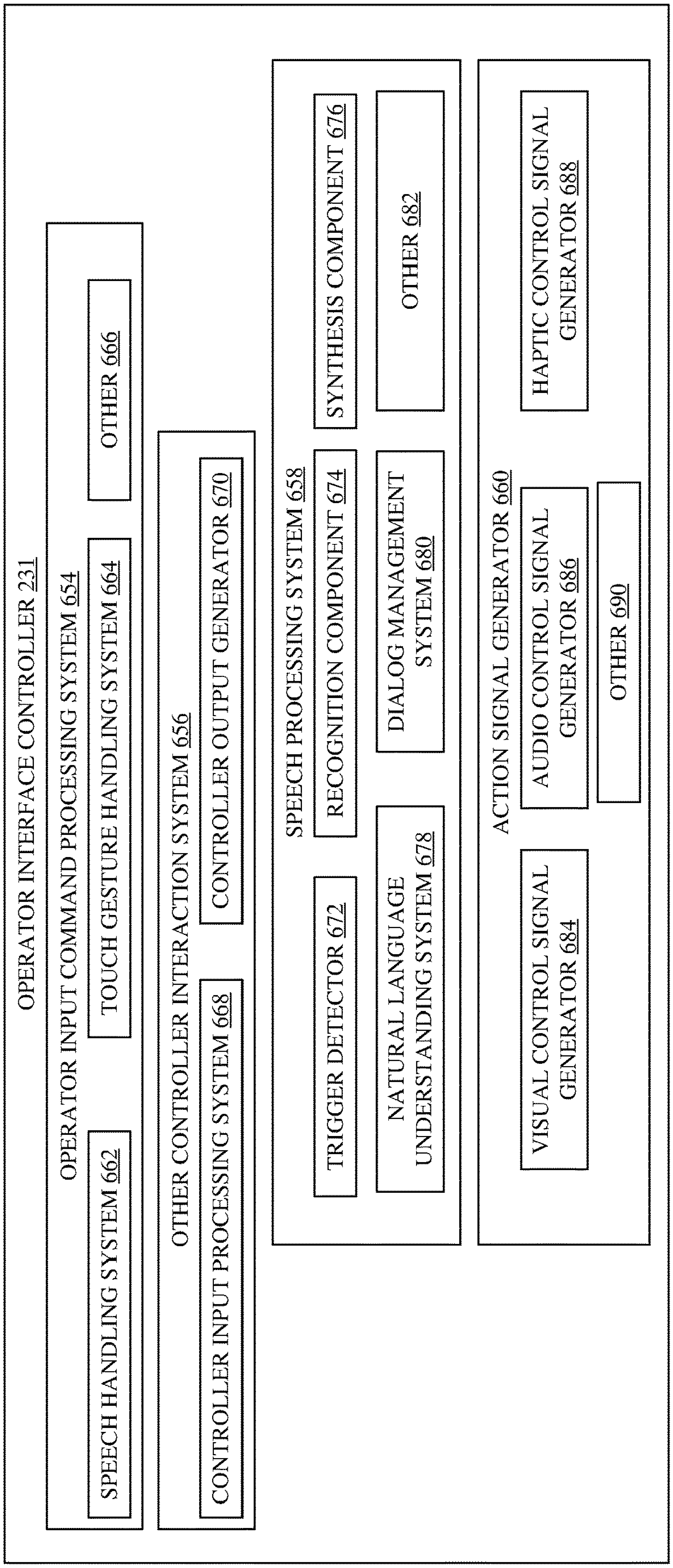
OPERATOR INTERFACE CONTROLLER 231
OPERATOR INPUT COMMAND PROCESSING SYSTEM 654
SPEECH HANDLING SYSTEM 662
TOUCH GESTURE HANDLING SYSTEM 664
OTHER 666
OTHER CONTROLLER INTERACTION SYSTEM 656
CONTROLLER INPUT PROCESSING SYSTEM 668
CONTROLLER OUTPUT GENERATOR 670
SPEECH PROCESSING SYSTEM 658
TRIGGER DETECTOR 672
RECOGNITION COMPONENT 674
SYNTHESIS COMPONENT 676
NATURAL LANGUAGE UNDERSTANDING SYSTEM 678
DIALOG MANAGEMENT SYSTEM 680
OTHER 682
ACTION SIGNAL GENERATOR 660
VISUAL CONTROL SIGNAL GENERATOR 684
AUDIO CONTROL SIGNAL GENERATOR 686
OTHER 690
HAPTIC CONTROL SIGNAL GENERATOR 688

FIG. 11

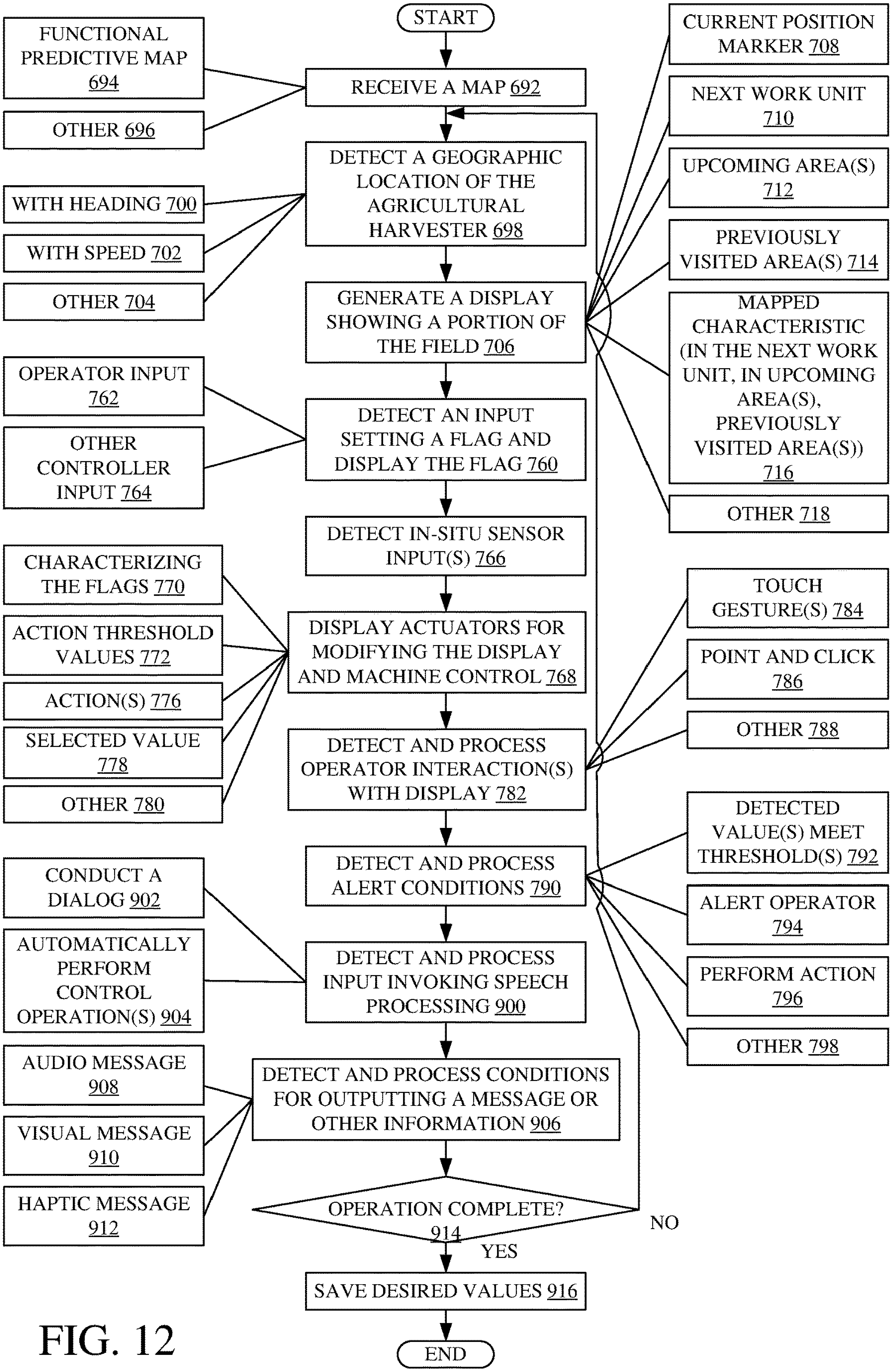
START
RECEIVE A MAP 692
FUNCTIONAL PREDICTIVE MAP 694
OTHER 696
DETECT A GEOGRAPHIC LOCATION OF THE AGRICULTURAL HARVESTER 698
WITH HEADING 700
WITH SPEED 702
OTHER 704
GENERATE A DISPLAY SHOWING A PORTION OF THE FIELD 706
CURRENT POSITION MARKER 708
NEXT WORK UNIT 710
UPCOMING AREA(S) 712
PREVIOUSLY VISITED AREA(S) 714
MAPPED CHARACTERISTIC (IN THE NEXT WORK UNIT, IN UPCOMING AREA(S), PREVIOUSLY VISITED AREA(S)) 716
OTHER 718
DETECT AN INPUT SETTING A FLAG AND DISPLAY THE FLAG 760
OPERATOR INPUT 762
OTHER CONTROLLER INPUT 764
DETECT IN-SITU SENSOR INPUT(S) 766
DISPLAY ACTUATORS FOR MODIFYING THE DISPLAY AND MACHINE CONTROL 768
CHARACTERIZING THE FLAGS 770
ACTION THRESHOLD VALUES 772
ACTION(S) 776
SELECTED VALUE 778
OTHER 780
DETECT AND PROCESS OPERATOR INTERACTION(S) WITH DISPLAY 782
TOUCH GESTURE(S) 784
POINT AND CLICK 786
OTHER 788
DETECT AND PROCESS ALERT CONDITIONS 790
DETECTED VALUE(S) MEET THRESHOLD(S) 792
ALERT OPERATOR 794
PERFORM ACTION 796
OTHER 798
DETECT AND PROCESS INPUT INVOKING SPEECH PROCESSING 900
CONDUCT A DIALOG 902
AUTOMATICALLY PERFORM CONTROL OPERATION(S) 904
DETECT AND PROCESS CONDITIONS FOR OUTPUTTING A MESSAGE OR OTHER INFORMATION 906
AUDIO MESSAGE 908
VISUAL MESSAGE 910
HAPTIC MESSAGE 912
OPERATION COMPLETE? 914
NO
YES
SAVE DESIRED VALUES 916
END

FIG. 12

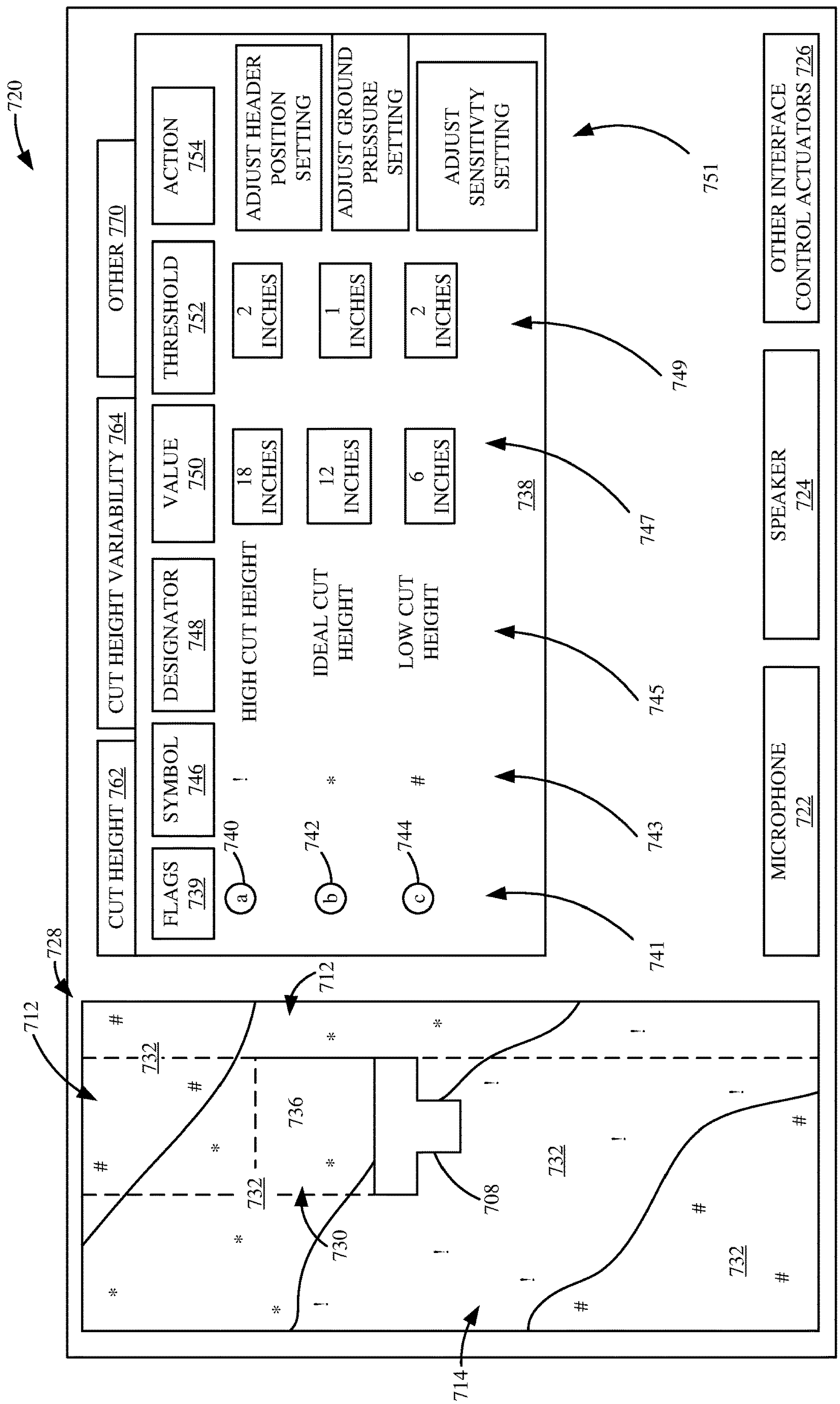
720
CUT HEIGHT 762
CUT HEIGHT VARIABILITY 764
OTHER 770
FLAGS 739
SYMBOL 746
DESIGNATOR 748
VALUE 750
THRESHOLD 752
ACTION 754
a
740
!
HIGH CUT HEIGHT
18 INCHES
2 INCHES
ADJUST HEADER POSITION SETTING
b
742
*
IDEAL CUT HEIGHT
12 INCHES
1 INCHES
ADJUST GROUND PRESSURE SETTING
c
744
#
LOW CUT HEIGHT
6 INCHES
2 INCHES
ADJUST SENSITIVTY SETTING
738
741
743
745
747
749
751
MICROPHONE 722
SPEAKER 724
OTHER INTERFACE CONTROL ACTUATORS 726
728
712
732
736
730
708
714

FIG. 13

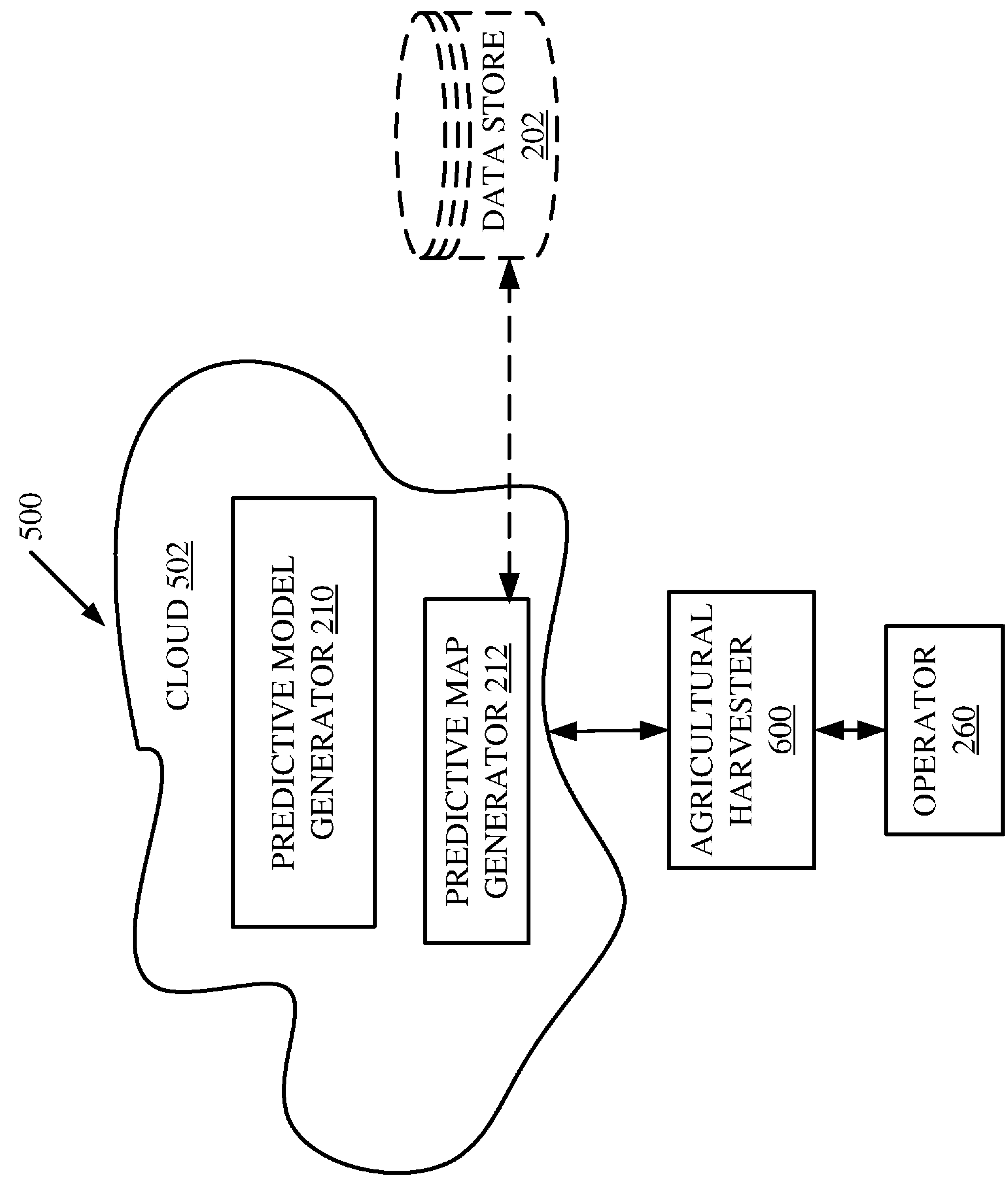
500
CLOUD 502
PREDICTIVE MODEL GENERATOR 210
PREDICTIVE MAP GENERATOR 212
DATA STORE 202
AGRICULTURAL HARVESTER 600
OPERATOR 260

FIG. 14

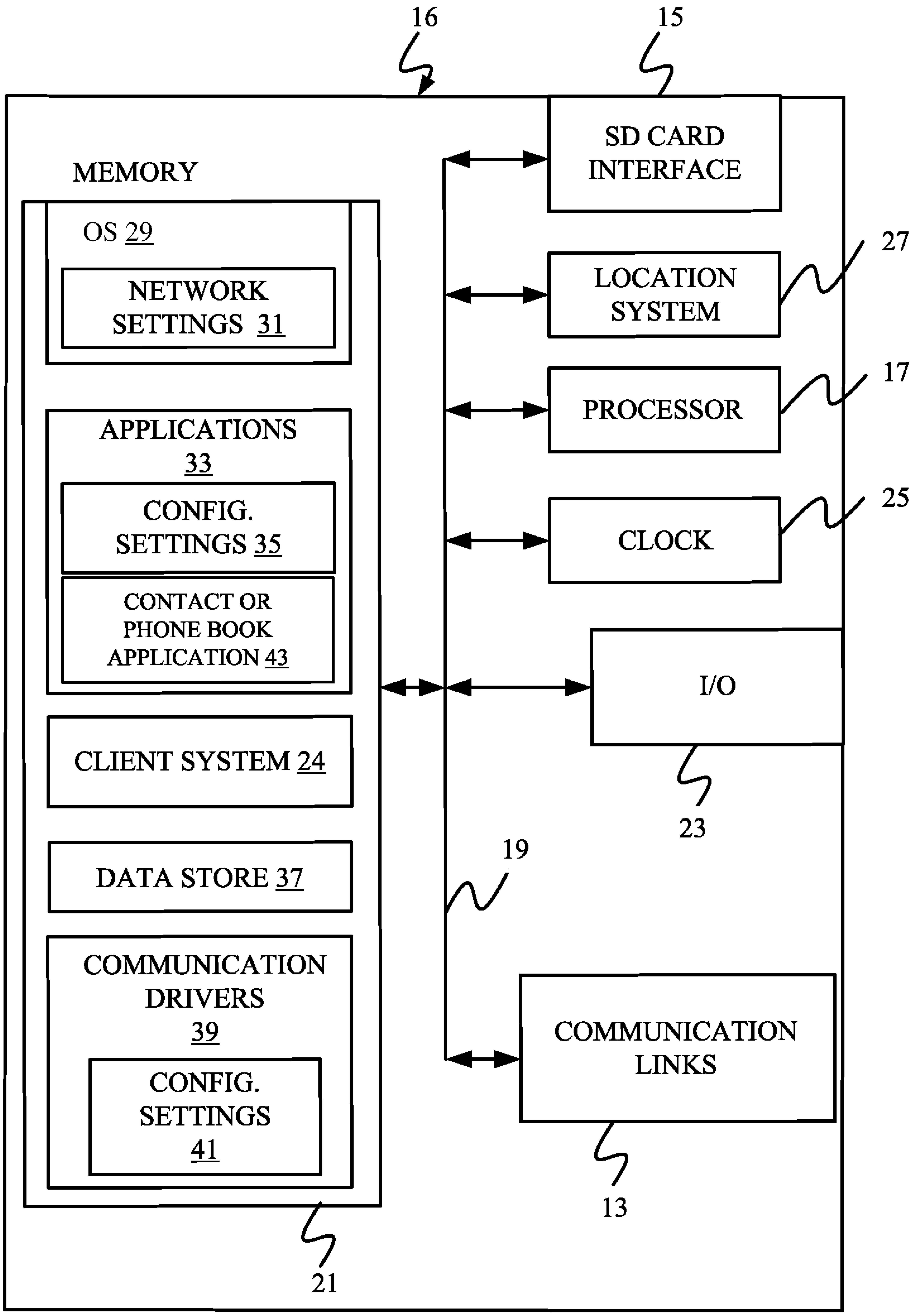
16
15
MEMORY
OS 29
NETWORK SETTINGS 31
APPLICATIONS 33
CONFIG. SETTINGS 35
CONTACT OR PHONE BOOK APPLICATION 43
CLIENT SYSTEM 24
DATA STORE 37
COMMUNICATION DRIVERS 39
CONFIG. SETTINGS 41
21
SD CARD INTERFACE
LOCATION SYSTEM
27
PROCESSOR
17
CLOCK
25
I/O
23
19
COMMUNICATION LINKS
13

FIG. 15

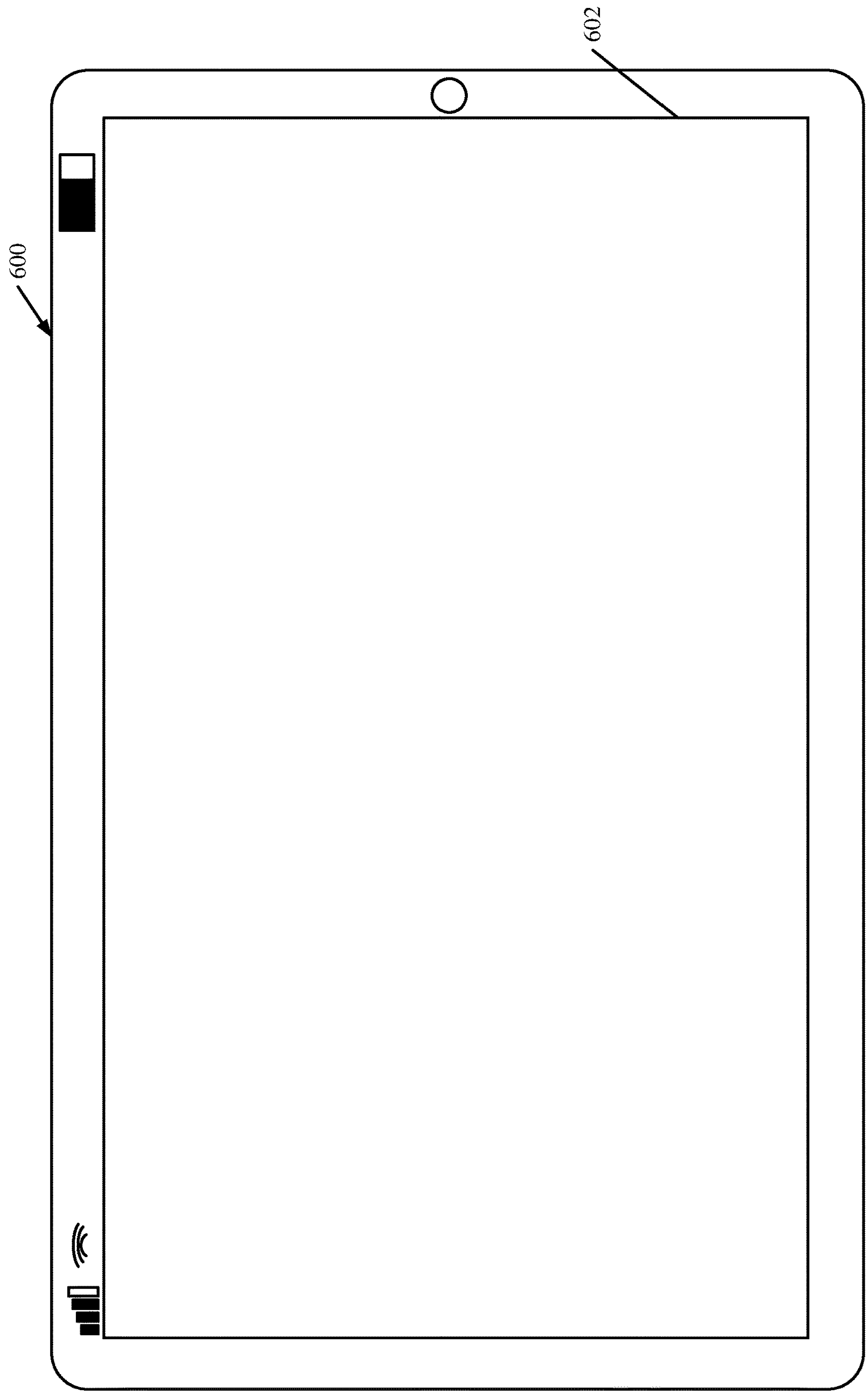

FIG. 16

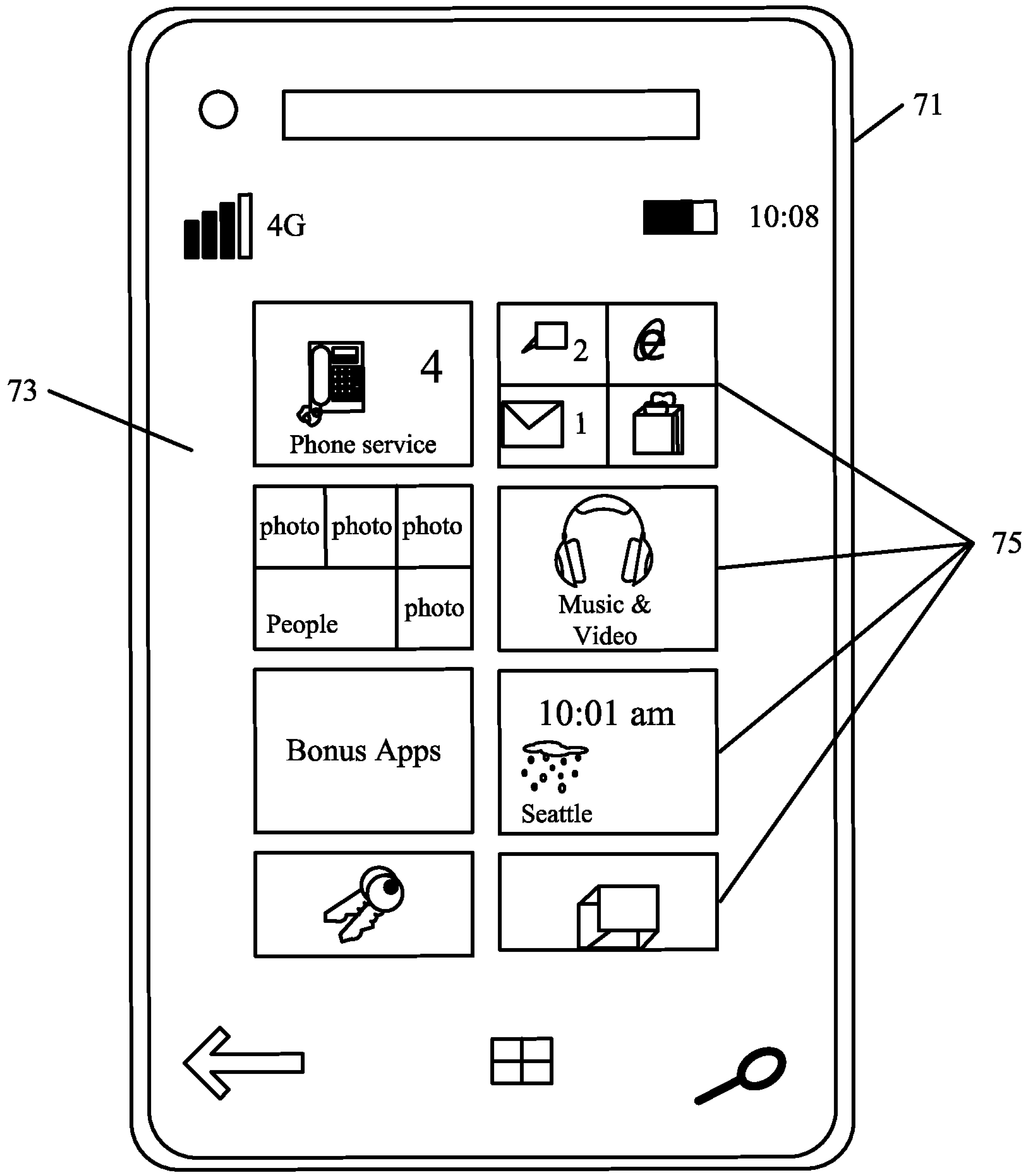
71
4G
10:08
73
2
1
4
Phone service
photo
photo
photo
People
photo
Music &
Video
75
Bonus Apps
10:01 am
Seattle

FIG. 17

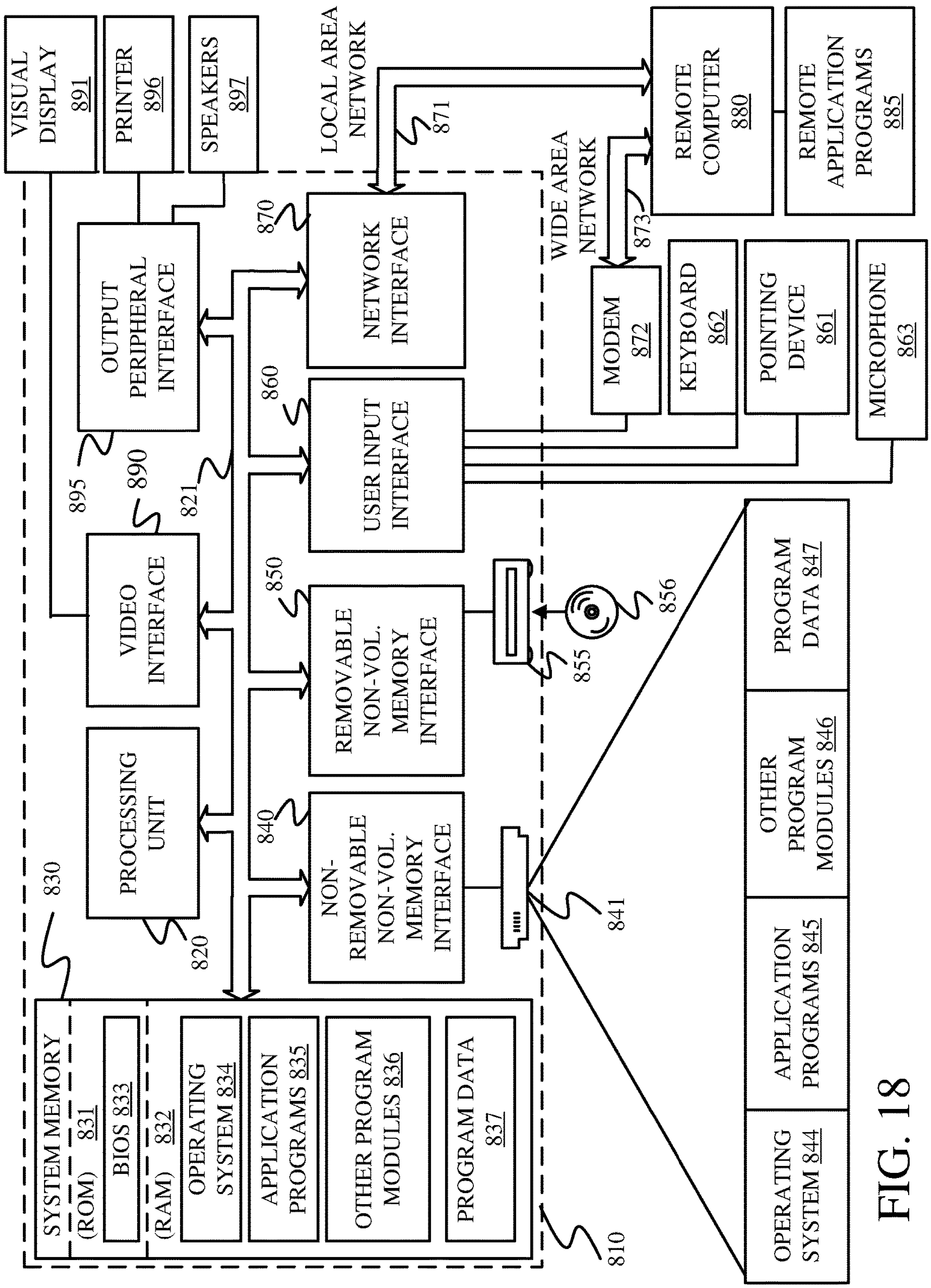
VISUAL DISPLAY 891
PRINTER 896
SPEAKERS 897
LOCAL AREA NETWORK
871
REMOTE COMPUTER 880
REMOTE APPLICATION PROGRAMS 885
WIDE AREA NETWORK
873
OUTPUT PERIPHERAL INTERFACE
870
NETWORK INTERFACE
MODEM 872
KEYBOARD 862
POINTING DEVICE 861
MICROPHONE 863
860
USER INPUT INTERFACE
895
890
821
VIDEO INTERFACE
850
REMOVABLE NON-VOL. MEMORY INTERFACE
856
855
830
PROCESSING UNIT
840
NON-REMOVABLE NON-VOL. MEMORY INTERFACE
841
820
PROGRAM DATA 847
OTHER PROGRAM MODULES 846
APPLICATION PROGRAMS 845
OPERATING SYSTEM 844
SYSTEM MEMORY
(ROM) 831
BIOS 833
(RAM) 832
OPERATING SYSTEM 834
APPLICATION PROGRAMS 835
OTHER PROGRAM MODULES 836
PROGRAM DATA 837
810

FIG. 18

PREDICTIVE MAP GENERATION AND CONTROL SYSTEM FOR AN AGRICULTURAL WORK MACHINE

FIELD OF THE DESCRIPTION

The present description relates to agricultural machines, forestry machines, construction machines and turf management machines.

BACKGROUND

There are a wide variety of different types of agricultural machines. Some agricultural machines include harvesters, such as combine harvesters, sugar cane harvesters, cotton harvesters, self-propelled forage harvesters, and windrowers. Some harvesters can also be fitted with different types of heads to harvest different types of crops.

A variety of different conditions in fields have a number of deleterious effects on the harvesting operation. Therefore, an operator may attempt to modify control of the harvester, upon encountering such conditions during the harvesting operation.

The discussion above is merely provided for general background information and is not intended to be used as an aid in determining the scope of the claimed subject matter.

SUMMARY

One or more information maps are obtained by an agricultural work machine. The one or more information maps map one or more agricultural characteristic values at different geographic locations of a field. An in-situ sensor on the agricultural work machine senses an agricultural characteristic as the agricultural work machine moves through the field. A predictive map generator generates a predictive map that predicts a predictive agricultural characteristic at different locations in the field based on a relationship between the values in the one or more information maps and the agricultural characteristic sensed by the in-situ sensor. The predictive map can be output and used in automated machine control.

This Summary is provided to introduce a selection of concepts in a simplified form that are further described below in the Detailed Description. This Summary is not intended to identify key features or essential features of the claimed subject matter, nor is it intended to be used as an aid in determining the scope of the claimed subject matter. The claimed subject matter is not limited to examples that solve any or all disadvantages noted in the background.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** is a partial pictorial, partial schematic illustration of one example of a combine harvester.

FIG. **2** is a block diagram showing some portions of an agricultural harvester in more detail, according to some examples of the present disclosure.

FIGS. **3**A-**3**B (collectively referred to herein as FIG. **3**) show a flow diagram illustrating an example of operation of an agricultural harvester in generating a map.

FIG. **4**A is a block diagram showing one example of a predictive model generator and a predictive map generator.

FIG. **4**B is a block diagram showing one example of a predictive model generator and a predictive map generator.

FIG. **5** is a flow diagram showing an example of operation of an agricultural harvester in receiving a map, detecting a characteristic, and generating a functional predictive map for use in controlling the agricultural harvester during a harvesting operation.

FIG. **6**A is a block diagram showing one example of a predictive model generator and a predictive map generator.

FIG. **6**B is a block diagram showing some examples of in-situ sensors.

FIG. **7** shows a flow diagram illustrating one example of operation of an agricultural harvester involving generating a functional predictive map using a prior information map and an in-situ sensor input.

FIG. **8** is a block diagram showing one example of a control zone generator.

FIG. **9** is a flow diagram illustrating one example of the operation of the control zone generator shown in FIG. **8**.

FIG. **10** illustrates a flow diagram showing an example of operation of a control system in selecting a target settings value to control an agricultural harvester.

FIG. **11** is a block diagram showing one example of an operator interface controller.

FIG. **12** is a flow diagram illustrating one example of an operator interface controller.

FIG. **13** is a pictorial illustration showing one example of an operator interface display.

FIG. **14** is a block diagram showing one example of an agricultural harvester in communication with a remote server environment.

FIGS. **15**-**17** show examples of mobile devices that can be used in an agricultural harvester.

FIG. **18** is a block diagram showing one example of a computing environment that can be used in an agricultural harvester.

DETAILED DESCRIPTION

For the purposes of promoting an understanding of the principles of the present disclosure, reference will now be made to the examples illustrated in the drawings, and specific language will be used to describe the same. It will nevertheless be understood that no limitation of the scope of the disclosure is intended. Any alterations and further modifications to the described devices, systems, methods, and any further application of the principles of the present disclosure are fully contemplated as would normally occur to one skilled in the art to which the disclosure relates. In particular, it is fully contemplated that the features, components, and/or steps described with respect to one example may be combined with the features, components, and/or steps described with respect to other examples of the present disclosure.

In some examples, the present description relates to using in-situ data taken concurrently with an agricultural operation, in combination with prior data, to generate a predictive map and, more particularly, a predictive speed map. In some examples, the predictive speed map can be used to control an agricultural work machine, such as an agricultural harvester. As discussed above, it may improve the performance of the agricultural harvester to control the speed of the agricultural harvester when the agricultural harvester engages different conditions in the field. For instance, if the crops have reached maturity, the weeds may still be green, thus increasing the moisture content of the biomass that is encountered by the agricultural harvester. This problem may be exacerbated when the weed patches are wet (such as shortly after a rainfall or when weed patches contain dew) and before the weeds have had a chance to dry. Thus, when the agricultural harvester encounters an area of increased biomass, the operator may slow the speed of the agricultural harvester to maintain a constant feed rate of material through the agricultural harvester. Maintaining a constant feed rate may maintain the performance of the agricultural harvester.

Performance of an agricultural harvester may be deleteriously affected based on a number of different criteria. Such different criteria may include changes in biomass, crop state, topography, soil properties, and seeding characteristics, or other conditions. Therefore, it may also be useful to control the speed of the agricultural harvester based on other conditions that may be present in the field. For example, the performance of the agricultural harvester may be maintained at an acceptable level by controlling the speed of the agricultural harvester based on the biomass encountered by the agricultural harvester, the crop state of the crop being harvested, the topography of the field being harvested, soil properties of soil in the field being harvested, seeding characteristics in the field being harvested, yield in the field being harvested, or other conditions that are present in the field.

Some current systems provide vegetative index maps. A vegetative index map illustratively maps vegetative index values (which may be indicative of vegetative growth) across different geographic locations in a field of interest. One example of a vegetative index includes a normalized difference vegetation index (NDVI). There are many other vegetative indices that are within the scope of the present disclosure. In some examples, a vegetative index may be derived from sensor readings of one or more bands of electromagnetic radiation reflected by the plants. Without limitations, these bands may be in the microwave, infrared, visible or ultraviolet portions of the electromagnetic spectrum.

A vegetative index map can be used to identify the presence and location of vegetation. In some examples, these maps enable vegetation to be identified and georeferenced in the presence of bare soil, crop residue, or other plants, including crop or other weeds.

In some examples, a biomass map is provided. A biomass map illustratively maps a measure of biomass in the field being harvested at different locations in the field. A biomass map may be generated from vegetative index values, from historically measured or estimated biomass levels, from images or other sensor readings taken during a previous operation in the field, or in other ways. In some examples, biomass may be adjusted by a factor representing a portion of total biomass passing through the agricultural harvester. For corn, this factor is typically around 50%. For moisture in harvested crop material, this factor is typically 10%-30%. In some examples, the factor may represent a portion of weed material or weed seeds. In some examples, the factor may represent a portion of one crop in an intercrop mix.

In some examples, a crop state map is provided. Crop state may define whether the crop is down, standing, partially down, the orientation of down or partially down crop relative to the ground surface or to a compass direction, and other things. A crop state map illustratively maps the crop state in the field being harvested at different locations in the field. A crop state map may be generated from aerial or other images of the field, from images or other sensor readings taken during a prior operation in the field or in other ways prior to harvesting.

In some examples, a seeding map is provided. A seeding map may map seeding characteristics such as seed locations, seed variety, or seed population to different locations in the field. The seeding map may be generated during a past seed planting operation in the field. The seeding map may be derived from control signals used by a seeder when planting seeds or from sensors on the seeder that confirm that a seed was metered or planted. Seeders may also include geographic position sensors that geolocate the seed characteristics on the field.

In some examples, a soil property map is provided. A soil property map illustratively maps a measure of one or more soil properties such as soil type, soil chemical constituents, soil structure, residue coverage, tillage history, or soil moisture in the field being harvested at different locations in the field. A soil properties map may be generated from vegetative index values, from historically measured or estimated soil properties, from images or other sensor readings taken during a previous operation in the field, or in other ways.

In some examples, other prior information maps are provided. Such prior information maps can include a topographic map of the field being harvested, a predictive yield map for the field being harvested, or other prior information maps.

In some examples, the present description relates to using in-situ data taken concurrently with an agricultural operation, in combination with data from a map, to generate a predictive map, and more particularly, a predictive cut height characteristic map. In some examples, the predictive cut height characteristic map can be used to control an agricultural work machine, such as an agricultural harvester. The predictive cut height characteristic map can include georeferenced predicted cut height or cut height variability values. In such examples, the present discussion also includes receiving, in addition to prior information maps, such as a prior topographic map, predictive maps that predict a characteristic based on a prior information map and a relationship to an in-situ sensor output. In one example, the predictive map is a predictive speed map. In one example, the predictive speed map is the functional predictive speed map described herein. In other examples, the predictive speed map can be created based on other prior information maps or generated in other ways as well.

The present discussion thus proceeds with respect to systems that receive one or more maps of a field or a map generated during a prior operation and also use an in-situ sensor to detect a variable indicative of one or more characteristics. The systems generate a model that models a relationship between the values on the one or more received maps and the output values from the in-situ sensor. The model is used to generate a functional predictive map that predicts, for example, a cut height or a cut height variability at different locations in the field. The functional predictive map, generated during the harvesting operation, can be presented to an operator or other user or used in automatically controlling an agricultural harvester during the harvesting operation or both.

An agricultural harvester is often fitted with a header that is movable (such as vertically moveable and rotatably moveable about one or more axis, such as in pitch (e.g., a tilt fore-to-aft) or roll (e.g., a tilt side-to-side across width of header), relative to the ground or another feature. For instance, one or more hydraulic actuators (or other actuators) are coupled between the feeder house and the frame of the agricultural harvester, though they could be coupled at other locations. The one or more hydraulic actuators can actuate movement of the header, such as to raise and lower the header. In some scenarios, the agricultural harvester is operated so that the header maintains a desired relationship relative to a feature, such as the surface of the field or portion of the agricultural harvester. For example, the one or more hydraulic actuators may be used to maintain the header at a selected distance from, height above, angle relative to, etc., the surface of the field. The operator of the agricultural harvester may set an initial height setting to establish a height, above the surface of the field, at which the operator wishes the header to be maintained during operation. The height of the header above the field, in addition to other positional settings (e.g., roll, pitch, etc.) determines a cut height. The cut height is the height at which vegetation on the field will be cut. A control system or, in some examples, the operator detects variables indicative of a header height or a cut height and controls the actuators that actuate movement of the header to move the header in order to maintain the desired height. The variables may be detected by sensing with the use of one or more sensors.

A field may have changes in topographic characteristics, such as changes in elevation, that require adjustment to the header of the agricultural harvester in order to maintain the desired cut height as the agricultural harvester moves through the field. These changes in topography may come upon the harvester too quickly, thereby preventing the effective movement of the header. For example, the harvester may be traveling at a speed that does not allow for timely adjustment of the header. This inability to timely adjust the header at a particular speed of the agricultural harvester may be the result of, for example, machine actuator response capabilities (e.g., response speed), sensor capabilities, or human operator capabilities. As a result, the header may strike the ground, cut vegetation undesirably, as well as other deleterious effects.

The present description thus proceeds with respect to systems that receive a map, such as a topographic map, a predictive speed map, or both. The system includes in-situ sensors capable of detecting a height of the header, a cut height, or both. The system further includes a model generator that identifies a relationship between the values in the received map (e.g., topographic characteristic values and speed values) and the characteristics (e.g., cut height, cut height variability, etc.) detected by the in-situ sensors. The model generator generates a predictive cut height characteristic model. The cut height characteristic model is used by a predictive map generator to generate a functional predictive cut height characteristic map that maps predictive cut height characteristic values. The functional predictive cut height characteristic map, generated during the harvesting operation, can be presented to an operator or other user or used in automatically controlling an agricultural harvester during the harvesting operation or both.

FIG. **1** is a partial pictorial, partial schematic, illustration of a self-propelled agricultural harvester **100**. In the illustrated example, agricultural harvester **100** is a combine harvester. Further, although combine harvesters are provided as examples throughout the present disclosure, it will be appreciated that the present description is also applicable to other types of harvesters, such as cotton harvesters, sugarcane harvesters, self-propelled forage harvesters, windrowers, or other agricultural work machines. Consequently, the present disclosure is intended to encompass the various types of harvesters described and is, thus, not limited to combine harvesters. Moreover, the present disclosure is directed to other types of work machines, such as agricultural seeders and sprayers, construction equipment, forestry equipment, and turf management equipment where generation of a predictive map may be applicable. Consequently, the present disclosure is intended to encompass these various types of harvesters and other work machines and is, thus, not limited to combine harvesters.

As shown in FIG. **1**, agricultural harvester **100** illustratively includes an operator compartment **101**, which can have a variety of different operator interface mechanisms, for controlling agricultural harvester **100**. Agricultural harvester **100** includes front-end equipment, such as a header **102**, and a cutter generally indicated at **104**. Agricultural harvester **100** also includes a feeder house **106**, a feed accelerator **108**, and a thresher generally indicated at **110**. The feeder house **106** and the feed accelerator **108** form part of a material handling subsystem **125**. Header **102** is pivotally coupled to a frame **103** of agricultural harvester **100** along pivot axis **105**. One or more actuators **107** drive movement of header **102** about axis **105** in the direction generally indicated by arrow **109**. Thus, a vertical position of header **102** (the header height) above ground **111** over which the header **102** travels is controllable by actuating actuator **107**. While not shown in FIG. **1**, agricultural harvester **100** may also include one or more actuators that operate to apply a tilt angle, a roll angle, or both to the header **102** or portions of header **102**. Tilt refers to an angle at which the cutter **104** engages the crop. The tilt angle is increased, for example, by controlling header **102** to point a distal edge **113** of cutter **104** more toward the ground. The tilt angle is decreased by controlling header **102** to point the distal edge **113** of cutter **104** more away from the ground. The roll angle refers to the orientation of header **102** about the front-to-back longitudinal axis of agricultural harvester **100**.

Thresher **110** illustratively includes a threshing rotor **112** and a set of concaves **114**. Further, agricultural harvester **100** also includes a separator **116**. Agricultural harvester **100** also includes a cleaning subsystem or cleaning shoe (collectively referred to as cleaning subsystem **118**) that includes a cleaning fan **120**, chaffer **122**, and sieve **124**. The material handling subsystem **125** also includes discharge beater **126**, tailings elevator **128**, clean grain elevator **130**, as well as unloading auger **134** and spout **136**. The clean grain elevator moves clean grain into clean grain tank **132**. Agricultural harvester **100** also includes a residue subsystem **138** that can include chopper **140** and spreader **142**. Agricultural harvester **100** also includes a propulsion subsystem that includes an engine that drives ground engaging components **144**, such as wheels or tracks. In some examples, a combine harvester within the scope of the present disclosure may have more than one of any of the subsystems mentioned above. In some examples, agricultural harvester **100** may have left and right cleaning subsystems, separators, etc., which are not shown in FIG. **1**.

In operation, and by way of overview, agricultural harvester **100** illustratively moves through a field in the direction indicated by arrow **147**. As agricultural harvester **100** moves, header **102** (and the associated reel **164**) engages the crop to be harvested and gathers the crop toward cutter **104**. An operator of agricultural harvester **100** can be a local human operator, a remote human operator, or an automated system. An operator command is a command by an operator. The operator of agricultural harvester **100** may determine one or more of a height setting, a tilt angle setting, or a roll angle setting for header **102**. For example, the operator inputs a setting or settings to a control system, described in more detail below, that controls actuator **107**. The control system may also receive a setting from the operator for establishing the tilt angle and roll angle of the header **102** and implement the inputted settings by controlling associated actuators, not shown, that operate to change the tilt angle and roll angle of the header **102**. The actuator **107** maintains header **102** at a height above ground **111** based on a height setting and, where applicable, at desired tilt and roll angles. Each of the height, roll, and tilt settings may be implemented independently of the others. The control system responds to header error (e.g., the difference between the height setting and measured height of header **104** above ground **111** and, in some examples, tilt angle and roll angle errors) with a responsiveness that is determined based on a selected sensitivity level. If the sensitivity level is set at a greater level of sensitivity, the control system responds to smaller header position errors, and attempts to reduce the detected errors more quickly than when the sensitivity is at a lower level of sensitivity.

Returning to the description of the operation of agricultural harvester **100**, after crops are cut by cutter **104**, the severed crop material is moved through a conveyor in feeder house **106** toward feed accelerator **108**, which accelerates the crop material into thresher **110**. The crop material is threshed by rotor **112** rotating the crop against concaves **114**. The threshed crop material is moved by a separator rotor in separator **116** where a portion of the residue is moved by discharge beater **126** toward the residue subsystem **138**. The portion of residue transferred to the residue subsystem **138** is chopped by residue chopper **140** and spread on the field by spreader **142**. In other configurations, the residue is released from the agricultural harvester **100** in a windrow. In other examples, the residue subsystem **138** can include weed seed eliminators (not shown) such as seed baggers or other seed collectors, or seed crushers or other seed destroyers.

Grain falls to cleaning subsystem **118**. Chaffer **122** separates some larger pieces of material from the grain, and sieve **124** separates some of finer pieces of material from the clean grain. Clean grain falls to an auger that moves the grain to an inlet end of clean grain elevator **130**, and the clean grain elevator **130** moves the clean grain upwards, depositing the clean grain in clean grain tank **132**. Residue is removed from the cleaning subsystem **118** by airflow generated by cleaning fan **120**. Cleaning fan **120** directs air along an airflow path upwardly through the sieves and chaffers. The airflow carries residue rearwardly in agricultural harvester **100** toward the residue handling subsystem **138**.

Tailings elevator **128** returns tailings to thresher **110** where the tailings are re-threshed. Alternatively, the tailings also may be passed to a separate re-threshing mechanism by a tailings elevator or another transport device where the tailings are re-threshed as well.

FIG. **1** also shows that, in one example, agricultural harvester **100** includes machine speed sensor **146**, one or more separator loss sensors **148**, a clean grain camera **150**, a forward looking image capture mechanism **151**, which may be in the form of a stereo or mono camera, and one or more loss sensors **152** provided in the cleaning subsystem **118**.

Machine speed sensor **146** senses the travel speed of agricultural harvester **100** over the ground. Machine speed sensor **146** may sense the travel speed of the agricultural harvester **100** by sensing the speed of rotation of the ground engaging components (such as wheels or tracks), a drive shaft, an axel, or other components. In some instances, the travel speed may be sensed using a positioning system, such as a global positioning system (GPS), a dead reckoning system, a long range navigation (LORAN) system, or a wide variety of other systems or sensors that provide an indication of travel speed.

Loss sensors **152** illustratively provide an output signal indicative of the quantity of grain loss occurring in both the right and left sides of the cleaning subsystem **118**. In some examples, sensors **152** are strike sensors which count grain strikes per unit of time or per unit of distance traveled to provide an indication of the grain loss occurring at the cleaning subsystem **118**. The strike sensors for the right and left sides of the cleaning subsystem **118** may provide individual signals or a combined or aggregated signal. In some examples, sensors **152** may include a single sensor as opposed to separate sensors provided for each cleaning subsystem **118**.

Separator loss sensor **148** provides a signal indicative of grain loss in the left and right separators, not separately shown in FIG. **1**. The separator loss sensors **148** may be associated with the left and right separators and may provide separate grain loss signals or a combined or aggregate signal. In some instances, sensing grain loss in the separators may also be performed using a wide variety of different types of sensors as well.

Agricultural harvester **100** may also include other sensors and measurement mechanisms. For instance, agricultural harvester **100** may include one or more of the following sensors: a header height sensor that senses a height of header **102** above ground **111**; a cut height sensor that senses a height at which vegetation on the field are cut; stability sensors that sense oscillation or bouncing motion (and amplitude) of agricultural harvester **100**; a residue setting sensor that is configured to sense whether agricultural harvester **100** is configured to chop the residue, produce a windrow, etc.; a cleaning shoe fan speed sensor to sense the speed of fan **120**; a concave clearance sensor that senses clearance between the rotor **112** and concaves **114**; a threshing rotor speed sensor that senses a rotor speed of rotor **112**; a chaffer clearance sensor that senses the size of openings in chaffer **122**; a sieve clearance sensor that senses the size of openings in sieve **124**; a material other than grain (MOG) moisture sensor that senses a moisture level of the MOG passing through agricultural harvester **100**; one or more machine setting sensors configured to sense various configurable settings of agricultural harvester **100**; a machine orientation sensor that senses the orientation of agricultural harvester **100**; and crop property sensors that sense a variety of different types of crop properties, such as crop type, crop moisture, and other crop properties. Crop property sensors may also be configured to sense characteristics of the severed crop material as the crop material is being processed by agricultural harvester **100**. For example, in some instances, the crop property sensors may sense grain quality such as broken grain, MOG levels; grain constituents such as starches and protein; and grain feed rate as the grain travels through the feeder house **106**, clean grain elevator **130**, or elsewhere in the agricultural harvester **100**. The crop property sensors may also sense the feed rate of biomass through feeder house **106**, through the separator **116** or elsewhere in agricultural harvester **100**. The crop property sensors may also sense the feed rate as a mass flow rate of grain through elevator **130** or through other portions of the agricultural harvester **100** or provide other output signals indicative of other sensed variables.

The header height sensor may take a wide variety of different forms. For instance, the header height sensor can be a potentiometer or angle encoders that sense the rotation of header or the angular position of header relative to the frame of agricultural harvester **100**. Knowing the dimensions of header **102** and agricultural harvester **100**, the height of header **102** above the field (e.g., ground **111**) can be determined using the sensor data. The header height sensors can also be sensors that directly sense the height of header **102** above the field. Example sensors that can directly sense a height of the header above the surface of the field include, but are not limited to, radar, lidar, ultrasonic sensors, laser sensors, or mechanical sensors.

In one example, the header height sensor can be a mechanical sensor assembly that includes a device coupled to the header and configured to contact the surface of the field and generate a sensor signal indicative of the height of the header relative to the surface of the field. Various other header height sensors are also contemplated herein. The header height outputs of the header height sensor may be processed, such as by aggregation or various other processing, such as statistical summary processing, to provide an indication of header height variability for a given area of the field. The header height variability can be indicative of a variation in header height for a given area. The header height variability can be expressed in various ways, such as an average header height for a particular area, an average header height deviation for a particular area, or variation for a particular area, as well as numerous other expressions.

Agricultural harvester **100** can also include cut height sensors in the form of optical sensors, such as a camera, as well as various other sensors, such as radar, lidar, ultrasonic, or laser, sensing devices. The cut height sensors are configured to detect characteristics indicative of a cut height, that is, the height at which vegetation is cut by the header. For example, the cut height sensors may detect a height of remaining crop stubble extending above the surface of the field (e.g., a height of remaining crop stalks) in an area of the field around agricultural harvester **100**, such as behind the agricultural harvester or behind components of the agricultural harvester, such as header **102**, relative to a direction of travel of the agricultural harvester, as an indication of cut height. Additionally, the cut height outputs of the cut height sensor may be processed, such as by aggregation, or various other processing, such as statistical summary processing, to provide an indication of cut height variability for a particular area of the field, such as an area behind the agricultural harvester **100**. The cut height variability can be indicative of a variation in cut height for a particular area of the field. The cut height variability can be expressed in various ways, such as an average cut height for a particular area, an average cut height deviation or variation for a particular area, as well as numerous other expressions.

In some examples, the output of the header height sensor can be used as an indication of cut height. For example, by knowing the height of header relative to the surface of the field, the height at which vegetation is cut can also be known or estimated.

Prior to describing how agricultural harvester **100** generates a functional predictive speed map, and uses the functional predictive speed map for control, a brief description of some of the items on agricultural harvester **100**, and their operation, will first be described. The description of FIGS. **2** and **3** describe receiving a general type of prior information map and combining information from the prior information map with a georeferenced sensor signal generated by an in-situ sensor, where the sensor signal is indicative of a characteristic in the field, such as characteristics of the field itself, crop characteristics of crop or grain present in the field, or characteristics of the agricultural harvester. Characteristics of the field may include, but are not limited to, characteristics of a field such as slope, weed intensity, weed type, soil moisture, surface quality; characteristics of crop properties such as crop height, crop moisture, crop density, crop state; characteristics of grain properties such as grain moisture, grain size, grain test weight; and characteristics of machine operation such as machine speed, outputs from different controllers, machine performance such as loss levels, job quality, fuel consumption, and power utilization. A relationship between the characteristic values obtained from in-situ sensor signals or values derived therefrom and the prior information map values is identified, and that relationship is used to generate a new functional predictive map. A functional predictive map predicts values at different geographic locations in a field, and one or more of those values may be used for controlling a machine, such as one or more subsystems of an agricultural harvester. In some instances, a functional predictive map can be presented to a user, such as an operator of an agricultural work machine, which may be an agricultural harvester. A functional predictive map may be presented to a user visually, such as via a display, haptically, or audibly. The user may interact with the functional predictive map to perform editing operations and other user interface operations. In some instances, a functional predictive map can be used for one or more of controlling an agricultural work machine, such as an agricultural harvester, presentation to an operator or other user, and presentation to an operator or user for interaction by the operator or user.

After the general approach is described with respect to FIGS. **2** and **3**, a more specific approach for generating a functional predictive that can be presented to an operator or user, or used to control agricultural harvester **100**, or both is described with respect to FIGS. **4** and **5**. Again, while the present discussion proceeds with respect to the agricultural harvester and, particularly, a combine harvester, the scope of the present disclosure encompasses other types of agricultural harvesters or other agricultural work machines.

FIG. **2** is a block diagram showing some portions of an example agricultural harvester **100**. FIG. **2** shows that agricultural harvester **100** illustratively includes one or more processors or servers **201**, data store **202**, geographic position sensor **204**, communication system **206**, and one or more in-situ sensors **208** that sense one or more agricultural characteristics of a field concurrent with a harvesting operation. An agricultural characteristic can include any characteristic that can have an effect of the harvesting operation. Some examples of agricultural characteristics include characteristics of the harvesting machine, the field, the plants on the field, and the weather. Other types of agricultural characteristics are also included. The in-situ sensors **208** generate values corresponding to the sensed characteristics. The agricultural harvester **100** also includes a predictive model or relationship generator (collectively referred to hereinafter as "predictive model generator **210**"), predictive map generator **212**, control zone generator **213**, control system **214**, one or more controllable subsystems **216**, and an operator interface mechanism **218**. The agricultural harvester **100** can also include a wide variety of other agricultural harvester functionality **220**. The in-situ sensors **208** include, for example, on-board sensors **222**, remote sensors **224**, and other sensors **226** that sense characteristics of a field during the course of an agricultural operation. Predictive model generator **210** illustratively includes a prior information variable-to-in-situ variable model generator **228**, and predictive model generator **210** can include other items **230**. Control system **214** includes communication system controller **229**, operator interface controller **231**, a settings controller **232**, path planning controller **234**, feed rate controller **236**, header and reel controller **238**, draper belt controller **240**, deck plate position controller **242**, residue system controller **244**, machine cleaning controller **245**, zone controller **247**, and system **214** can include other items **246**. Controllable subsystems **216** include machine and header actuators **248**, propulsion subsystem **250**, steering subsystem **252**, residue subsystem **138**, machine cleaning subsystem **254**, and subsystems **216** can include a wide variety of other subsystems **256**.

FIG. **2** also shows that agricultural harvester **100** can receive prior information map **258**. As described below, the prior information map **258** includes, for example, a vegetative index map, a biomass map, a crop state map, a topographic map, a soil property map, a seeding map, or a map from a prior operation. However, prior information map **258** may also encompass other types of data that were obtained prior to a harvesting operation or a map from a prior operation. FIG. **2** also shows that an operator **260** may operate the agricultural harvester **100**. The operator **260** interacts with operator interface mechanisms **218**. In some examples, operator interface mechanisms **218** may include joysticks, levers, a steering wheel, linkages, pedals, buttons, dials, keypads, user actuatable elements (such as icons, buttons, etc.) on a user interface display device, a microphone and speaker (where speech recognition and speech synthesis are provided), among a wide variety of other types of control devices. Where a touch sensitive display system is provided, operator **260** may interact with operator interface mechanisms **218** using touch gestures. These examples described above are provided as illustrative examples and are not intended to limit the scope of the present disclosure. Consequently, other types of operator interface mechanisms **218** may be used and are within the scope of the present disclosure.

Prior information map **258** may be downloaded onto agricultural harvester **100** and stored in data store **202**, using communication system **206** or in other ways. In some examples, communication system **206** may be a cellular communication system, a system for communicating over a wide area network or a local area network, a system for communicating over a near field communication network, or a communication system configured to communicate over any of a variety of other networks or combinations of networks. Communication system **206** may also include a system that facilitates downloads or transfers of information to and from a secure digital (SD) card or a universal serial bus (USB) card or both.

Geographic position sensor **204** illustratively senses or detects the geographic position or location of agricultural harvester **100**. Geographic position sensor **204** can include, but is not limited to, a global navigation satellite system (GNSS) receiver that receives signals from a GNSS satellite transmitter. Geographic position sensor **204** can also include a real-time kinematic (RTK) component that is configured to enhance the precision of position data derived from the GNSS signal. Geographic position sensor **204** can include a dead reckoning system, a cellular triangulation system, or any of a variety of other geographic position sensors.

In-situ sensors **208** may be any of the sensors described above with respect to FIG. **1**. In-situ sensors **208** include on-board sensors **222** that are mounted on-board agricultural harvester **100**. Such sensors may include, for instance, any of the sensors discussed above with respect to FIG. **1**, a perception sensor (e.g., a forward looking mono or stereo camera system and image processing system), image sensors that are internal to agricultural harvester **100** (such as the clean grain camera or cameras mounted to identify material that is exiting agricultural harvester **100** through the residue subsystem or from the cleaning subsystem). The in-situ sensors **208** also include remote in-situ sensors **224** that capture in-situ information. In-situ data include data taken from a sensor on-board the harvester or taken by any sensor where the data are detected during the harvesting operation.

Predictive model generator **210** generates a model that is indicative of a relationship between the values sensed by the in-situ sensor **208** and a metric mapped to the field by the prior information map **258**. For example, if the prior information map **258** maps a vegetative index value to different locations in the field, and the in-situ sensor **208** is sensing a value indicative of machine speed, then prior information variable-to-in-situ variable model generator **228** generates a predictive speed model that models the relationship between the vegetative index value and the machine speed value. The predictive speed model can also be generated based on vegetative index values from the prior information map **258** and multiple in-situ data values generated by in-situ sensors **208**. Then, predictive map generator **212** uses the predictive speed model generated by predictive model generator **210** to generate a functional predictive speed map that predicts the target machine speed sensed by the in-situ sensors **208** at different locations in the field based upon the prior information map **258**.

In some examples, the type of values in the functional predictive map **263** may be the same as the in-situ data type sensed by the in-situ sensors **208**. In some instances, the type of values in the functional predictive map **263** may have different units from the data sensed by the in-situ sensors **208**. In some examples, the type of values in the functional predictive map **263** may be different from the data type sensed by the in-situ sensors **208** but have a relationship to the type of data type sensed by the in-situ sensors **208**. For example, in some examples, the data type sensed by the in-situ sensors **208** may be indicative of the type of values in the functional predictive map **263**. In some examples, the type of data in the functional predictive map **263** may be different than the data type in the prior information map **258**. In some instances, the type of data in the functional predictive map **263** may have different units from the data in the prior information map **258**. In some examples, the type of data in the functional predictive map **263** may be different from the data type in the prior information map **258** but has a relationship to the data type in the prior information map **258**. For example, in some examples, the data type in the prior information map **258** may be indicative of the type of data in the functional predictive map **263**. In some examples, the type of data in the functional predictive map **263** is different than one of, or both of the in-situ data type sensed by the in-situ sensors **208** and the data type in the prior information map **258**. In some examples, the type of data in the functional predictive map **263** is the same as one of, or both of, of the in-situ data type sensed by the in-situ sensors **208** and the data type in prior information map **258**. In some examples, the type of data in the functional predictive map **263** is the same as one of the in-situ data type sensed by the in-situ sensors **208** or the data type in the prior information map **258**, and different than the other.

In an example, in which prior information map **258** is a vegetative index map and in-situ sensor **208** senses a value indicative of machine speed, predictive map generator **212** can use the vegetative index values in prior information map **258**, and the model generated by predictive model generator **210**, to generate a functional predictive map **263** that predicts the target machine speed at different locations in the field. Predictive map generator **212** thus outputs predictive map **264**.

As shown in FIG. **2**, predictive map **264** predicts the value of a sensed characteristic (sensed by in-situ sensors **208**), or a characteristic related to the sensed characteristic, at various locations across the field based upon a prior information value in prior information map **258** at those locations and using the predictive model. For example, if predictive model generator **210** has generated a predictive model indicative of a relationship between a vegetative index value and machine speed, then, given the vegetative index value at different locations across the field, predictive map generator **212** generates a predictive map **264** that predicts the target machine speed value at different locations across the field. The vegetative index value, obtained from the vegetative index map, at those locations and the relationship between vegetative index value and machine speed, obtained from the predictive model, are used to generate the predictive map **264**.

Some variations in the data types that are mapped in the prior information map **258**, the data types sensed by in-situ sensors **208**, and the data types predicted on the predictive map **264** will now be described.

In some examples, the data type in the prior information map **258** is different from the data type sensed by in-situ sensors **208**, yet the data type in the predictive map **264** is the same as the data type sensed by the in-situ sensors **208**. For instance, the prior information map **258** may be a vegetative index map, and the variable sensed by the in-situ sensors **208** may be yield. The predictive map **264** may then be a predictive yield map that maps predicted yield values to different geographic locations in the field. In another example, the prior information map **258** may be a vegetative index map, and the variable sensed by the in-situ sensors **208** may be crop height. The predictive map **264** may then be a predictive crop height map that maps predicted crop height values to different geographic locations in the field.

Also, in some examples, the data type in the prior information map **258** is different from the data type sensed by in-situ sensors **208**, and the data type in the predictive map **264** is different from both the data type in the prior information map **258** and the data type sensed by the in-situ sensors **208**. For instance, the prior information map **258** may be a vegetative index map, and the variable sensed by the in-situ sensors **208** may be crop height. The predictive map **264** may then be a predictive biomass map that maps predicted biomass values to different geographic locations in the field. In another example, the prior information map **258** may be a vegetative index map, and the variable sensed by the in-situ sensors **208** may be yield. The predictive map **264** may then be a predictive speed map that maps predicted harvester speed values to different geographic locations in the field.

In some examples, the prior information map **258** is from a prior pass through the field during a prior operation and the data type is different from the data type sensed by in-situ sensors **208**, yet the data type in the predictive map **264** is the same as the data type sensed by the in-situ sensors **208**. For instance, the prior information map **258** may be a seed population map generated during planting, and the variable sensed by the in-situ sensors **208** may be stalk size. The predictive map **264** may then be a predictive stalk size map that maps predicted stalk size values to different geographic locations in the field. In another example, the prior information map **258** may be a seeding hybrid map, and the variable sensed by the in-situ sensors **208** may be crop state such as standing crop or down crop. The predictive map **264** may then be a predictive crop state map that maps predicted crop state values to different geographic locations in the field.

In some examples, the prior information map **258** is from a prior pass through the field during a prior operation and the data type is the same as the data type sensed by in-situ sensors **208**, and the data type in the predictive map **264** is also the same as the data type sensed by the in-situ sensors **208**. For instance, the prior information map **258** may be a yield map generated during a previous year, and the variable sensed by the in-situ sensors **208** may be yield. The predictive map **264** may then be a predictive yield map that maps predicted yield values to different geographic locations in the field. In such an example, the relative yield differences in the georeferenced prior information map **258** from the prior year can be used by predictive model generator **210** to generate a predictive model that models a relationship between the relative yield differences on the prior information map **258** and the yield values sensed by in-situ sensors **208** during the current harvesting operation. The predictive model is then used by predictive map generator **210** to generate a predictive yield map.

In another example, the prior information map **258** may be a weed intensity map generated during a prior operation, such as from a sprayer, and the variable sensed by the in-situ sensors **208** may be weed intensity. The predictive map **264** may then be a predictive weed intensity map that maps predicted weed intensity values to different geographic locations in the field. In such an example, a map of the weed intensities at time of spraying is geo-referenced recorded and provided to agricultural harvester **100** as a prior information map **258** of weed intensity. In-situ sensors **208** can detect weed intensity at geographic locations in the field and predictive model generator **210** may then build a predictive model that models a relationship between weed intensity at time of harvest and weed intensity at time of spraying. This is because the sprayer will have impacted the weed intensity at time of spraying, but weeds may still crop up in similar areas again by harvest. However, the weed areas at harvest are likely to have different intensity based on timing of the harvest, weather, weed type, among other things.

In some examples, predictive map **264** can be provided to the control zone generator **213**. Control zone generator **213** groups adjacent portions of an area into one or more control zones based on data values of predictive map **264** that are associated with those adjacent portions. A control zone may include two or more contiguous portions of an area, such as a field, for which a control parameter corresponding to the control zone for controlling a controllable subsystem is constant. For example, a response time to alter a setting of controllable subsystems **216** may be inadequate to satisfactorily respond to changes in values contained in a map, such as predictive map **264**. In that case, control zone generator **213** parses the map and identifies control zones that are of a defined size to accommodate the response time of the controllable subsystems **216**. In another example, control zones may be sized to reduce wear from excessive actuator movement resulting from continuous adjustment. In some examples, there may be a different set of control zones for each controllable subsystem **216** or for groups of controllable subsystems **216**. The control zones may be added to the predictive map **264** to obtain predictive control zone map **265**. Predictive control zone map **265** can thus be similar to predictive map **264** except that map **265** includes control zone information defining the control zones. Thus, a functional predictive map **263**, as described herein, may or may not include control zones. Both predictive map **264** and predictive control zone map **265** are functional predictive maps **263**. In one example, a functional predictive map **263** does not include control zones, such as predictive map **264**. In another example, a functional predictive map **263** does include control zones, such as predictive control zone map **265**. In some examples, multiple crops may be simultaneously present in a field if an intercrop production system is implemented. In that case, predictive map generator **212** and control zone generator **213** are able to identify the location and characteristics of the two or more crops and then generate predictive map **264** and predictive control zone map **265** accordingly.

It will also be appreciated that control zone generator **213** can cluster values to generate control zones and the control zones can be added to predictive control zone map **265**, or a separate map, showing only the control zones that are generated. In some examples, the control zones may be used for controlling or calibrating agricultural harvester **100** or both. In other examples, the control zones may be presented to the operator **260** and used to control or calibrate agricultural harvester **100**, and, in other examples, the control zones may be presented to the operator **260** or another user or stored for later use.

Predictive map **264** or predictive control zone map **265** or both are provided to control system **214**, which generates control signals based upon the predictive map **264** or predictive control zone map **265** or both. In some examples, communication system controller **229** controls communication system **206** to communicate the predictive map **264** or predictive control zone map **265** or control signals based on the predictive map **264** or predictive control zone map **265** to other agricultural harvesters that are harvesting in the same field. In some examples, communication system controller **229** controls the communication system **206** to send the predictive map **264**, predictive control zone map **265**, or both to other remote systems.

Operator interface controller **231** is operable to generate control signals to control operator interface mechanisms **218**. The operator interface controller **231** is also operable to present the predictive map **264** or predictive control zone map **265** or other information derived from or based on the predictive map **264**, predictive control zone map **265**, or both to operator **260**. Operator **260** may be a local operator or a remote operator. As an example, controller **231** generates control signals to control a display mechanism to display one or both of predictive map **264** and predictive control zone map **265** for the operator **260**. Controller **231** may generate operator actuatable mechanisms that are displayed and can be actuated by the operator to interact with the displayed map. The operator can edit the map by, for example, correcting a weed type displayed on the map, based on the operator's observation. Settings controller **232** can generate control signals to control various settings on the agricultural harvester **100** based upon predictive map **264**, the predictive control zone map **265**, or both. For instance, settings controller **232** can generate control signals to control machine and header actuators **248**. In response to the generated control signals, the machine and header actuators **248** operate to control, for example, one or more of the sieve and chaffer settings, concave clearance, rotor settings, cleaning fan speed settings, header height, header functionality, reel speed, reel position, draper functionality (where agricultural harvester **100** is coupled to a draper header), corn header functionality, internal distribution control and other actuators **248** that affect the other functions of the agricultural harvester **100**. Path planning controller **234** illustratively generates control signals to control steering subsystem **252** to steer agricultural harvester **100** according to a desired path. Path planning controller **234** can control a path planning system to generate a route for agricultural harvester **100** and can control propulsion subsystem **250** and steering subsystem **252** to steer agricultural harvester **100** along that route. Feed rate controller **236** may receive a variety of different inputs indicative of a feed rate of material through agricultural harvester **100** and can control various subsystems, such as propulsion subsystem **250** and machine actuators **248**, to control the feed rate based upon the predictive map **264** or predictive control zone map **265** or both. For instance, as agricultural harvester **100** approaches a weed patch having an intensity value above a selected threshold, feed rate controller **236** may generate a control signal to control propulsion subsystem **252** to reduce the speed of agricultural harvester **100** to maintain constant feed rate of biomass through the agricultural harvester **100**. Header and reel controller **238** can generate control signals to control a header or a reel or other header functionality. Draper belt controller **240** can generate control signals to control a draper belt or other draper functionality based upon the predictive map **264**, predictive control zone map **265**, or both. Deck plate position controller **242** can generate control signals to control a position of a deck plate included on a header based on predictive map **264** or predictive control zone map **265** or both, and residue system controller **244** can generate control signals to control a residue subsystem **138** based upon predictive map **264** or predictive control zone map **265**, or both. Machine cleaning controller **245** can generate control signals to control machine cleaning subsystem **254**. For instance, based upon the different types of seeds or weeds passed through agricultural harvester **100**, a particular type of machine cleaning operation or a frequency with which a cleaning operation is performed may be controlled. Other controllers included on the agricultural harvester **100** can control other subsystems based on the predictive map **264** or predictive control zone map **265** or both as well.

FIGS. **3**A and **3**B (collectively referred to herein as FIG. **3**) show a flow diagram illustrating one example of the operation of agricultural harvester **100** in generating a predictive map **264** and predictive control zone map **265** based upon prior information map **258**.

At **280**, agricultural harvester **100** receives prior information map **258**. Examples of prior information map **258** or receiving prior information map **258** are discussed with respect to blocks **281**, **282**, **284** and **286**. As discussed above, prior information map **258** maps values of a variable, corresponding to a first characteristic, to different locations in the field, as indicated at block **282**. As indicated at block **281**, receiving the prior information map **258** may involve selecting one or more of a plurality of possible prior information maps that are available. For instance, one prior information map may be a vegetative index map generated from aerial imagery. Another prior information map may be a map generated during a prior pass through the field which may have been performed by a different machine performing a previous operation in the field, such as a sprayer or a planting machine or seeding machine or unmanned aerial vehicle (UAV) or other machine. The process by which one or more prior information maps are selected can be manual, semi-automated, or automated. The prior information map **258** is based on data collected prior to a current harvesting operation. This is indicated by block **284**. For instance, the data may be collected based on aerial images taken during a previous year, or earlier in the current growing season, or at other times. The data may be based on data detected in ways other than using aerial images. For instance, agricultural harvester **100** may be fitted with a sensor, such as an internal optical sensor, that identifies weed seeds or other types of material exiting agricultural harvester **100**. The weed seed or other data detected by the sensor during a previous year's harvest may be used as data used to generate the prior information map **258**. The sensed weed data or other data may be combined with other data to generate the prior information map **258**. For example, based upon a magnitude of the weed seeds exiting agricultural harvester **100** at different locations and based upon other factors, such as whether the seeds are being spread by a spreader or dropped in a windrow; the weather conditions, such as wind, when the seeds are being dropped or spread; drainage conditions which may move seeds around in the field; or other information, the location of those weed seeds can be predicted so that the prior information map **258** maps the predicted seed locations in the field. The data for the prior information map **258** can be transmitted to agricultural harvester **100** using communication system **206** and stored in data store **202**. The data for the prior information map **258** can be provided to agricultural harvester **100** using communication system **206** in other ways as well, and this is indicated by block **286** in the flow diagram of FIG. **3**. In some examples, the prior information map **258** can be received by communication system **206**.

Upon commencement of a harvesting operation, in-situ sensors **208** generate sensor signals indicative of one or more in-situ data values indicative of a characteristic, such as a speed characteristic, as indicated by block **288**. Examples of in-situ sensors **288** are discussed with respect to blocks **222**, **290**, and **226**. As explained above, the in-situ sensors **208** include on-board sensors **222**; remote in-situ sensors **224**, such as UAV-based sensors flown at a time to gather in-situ data, shown in block **290**; or other types of in-situ sensors, designated by in-situ sensors **226**. In some examples, data from on-board sensors is georeferenced using position, heading, or speed data from geographic position sensor **204**.

Predictive model generator **210** controls the prior information variable-to-in-situ variable model generator **228** to generate a model that models a relationship between the mapped values contained in the prior information map **258** and the in-situ values sensed by the in-situ sensors **208** as indicated by block **292**. The characteristics or data types represented by the mapped values in the prior information map **258** and the in-situ values sensed by the in-situ sensors **208** may be the same characteristics or data type or different characteristics or data types.

The relationship or model generated by predictive model generator **210** is provided to predictive map generator **212**. Predictive map generator **212** generates a predictive map **264** that predicts a value of the characteristic sensed by the in-situ sensors **208** at different geographic locations in a field being harvested, or a different characteristic that is related to the characteristic sensed by the in-situ sensors **208**, using the predictive model and the prior information map **258**, as indicated by block **294**.

It should be noted that, in some examples, the prior information map **258** may include two or more different maps or two or more different map layers of a single map. Each map layer may represent a different data type from the data type of another map layer or the map layers may have the same data type that were obtained at different times. Each map in the two or more different maps or each layer in the two or more different map layers of a map maps a different type of variable to the geographic locations in the field. In such an example, predictive model generator **210** generates a predictive model that models the relationship between the in-situ data and each of the different variables mapped by the two or more different maps or the two or more different map layers. Similarly, the in-situ sensors **208** can include two or more sensors each sensing a different type of variable. Thus, the predictive model generator **210** generates a predictive model that models the relationships between each type of variable mapped by the prior information map **258** and each type of variable sensed by the in-situ sensors **208**. Predictive map generator **212** can generate a functional predictive map **263** that predicts a value for each sensed characteristic sensed by the in-situ sensors **208** (or a characteristic related to the sensed characteristic) at different locations in the field being harvested using the predictive model and each of the maps or map layers in the prior information map **258**.

Predictive map generator **212** configures the predictive map **264** so that the predictive map **264** is actionable (or consumable) by control system **214**. Predictive map generator **212** can provide the predictive map **264** to the control system **214** or to control zone generator **213** or both. Some examples of different ways in which the predictive map **264** can be configured or output are described with respect to blocks **296**, **295**, **299** and **297**. For instance, predictive map generator **212** configures predictive map **264** so that predictive map **264** includes values that can be read by control system **214** and used as the basis for generating control signals for one or more of the different controllable subsystems of the agricultural harvester **100**, as indicated by block **296**.

Control zone generator **213** can divide the predictive map **264** into control zones based on the values on the predictive map **264**. Contiguously-geolocated values that are within a threshold value of one another can be grouped into a control zone. The threshold value can be a default threshold value, or the threshold value can be set based on an operator input, based on an input from an automated system, or based on other criteria. A size of the zones may be based on a responsiveness of the control system **214**, the controllable subsystems **216**, based on wear considerations, or on other criteria as indicated by block **295**. Predictive map generator **212** configures predictive map **264** for presentation to an operator or other user. Control zone generator **213** can configure predictive control zone map **265** for presentation to an operator or other user. This is indicated by block **299**. When presented to an operator or other user, the presentation of the predictive map **264** or predictive control zone map **265** or both may contain one or more of the predictive values on the predictive map **264** correlated to geographic location, the control zones on predictive control zone map **265** correlated to geographic location, and settings values or control parameters that are used based on the predicted values on map **264** or zones on predictive control zone map **265**. The presentation can, in another example, include more abstracted information or more detailed information. The presentation can also include a confidence level that indicates an accuracy with which the predictive values on predictive map **264** or the zones on predictive control zone map **265** conform to measured values that may be measured by sensors on agricultural harvester **100** as agricultural harvester **100** moves through the field. Further where information is presented to more than one location, an authentication and authorization system can be provided to implement authentication and authorization processes. For instance, there may be a hierarchy of individuals that are authorized to view and change maps and other presented information. By way of example, an on-board display device may show the maps in near real time locally on the machine, or the maps may also be generated at one or more remote locations, or both. In some examples, each physical display device at each location may be associated with a person or a user permission level. The user permission level may be used to determine which display markers are visible on the physical display device and which values the corresponding person may change. As an example, a local operator of machine **100** may be unable to see the information corresponding to the predictive map **264** or make any changes to machine operation. A supervisor, such as a supervisor at a remote location, however, may be able to see the predictive map **264** on the display but be prevented from making any changes. A manager, who may be at a separate remote location, may be able to see all of the elements on predictive map **264** and also be able to change the predictive map **264**. In some instances, the predictive map **264** accessible and changeable by a manager located remotely may be used in machine control. This is one example of an authorization hierarchy that may be implemented. The predictive map **264** or predictive control zone map **265** or both can be configured in other ways as well, as indicated by block **297**.

At block **298**, input from geographic position sensor **204** and other in-situ sensors **208** are received by the control system. Particularly, at block **300**, control system **214** detects an input from the geographic position sensor **204** identifying a geographic location of agricultural harvester **100**. Block **302** represents receipt by the control system **214** of sensor inputs indicative of trajectory or heading of agricultural harvester **100**, and block **304** represents receipt by the control system **214** of a speed of agricultural harvester **100**. Block **306** represents receipt by the control system **214** of other information from various in-situ sensors **208**.

At block **308**, control system **214** generates control signals to control the controllable subsystems **216** based on the predictive map **264** or predictive control zone map **265** or both and the input from the geographic position sensor **204** and any other in-situ sensors **208**. At block **310**, control system **214** applies the control signals to the controllable subsystems. It will be appreciated that the particular control signals that are generated, and the particular controllable subsystems **216** that are controlled, may vary based upon one or more different things. For example, the control signals that are generated and the controllable subsystems **216** that are controlled may be based on the type of predictive map **264** or predictive control zone map **265** or both that is being used. Similarly, the control signals that are generated and the controllable subsystems **216** that are controlled and the timing of the control signals can be based on various latencies of crop flow through the agricultural harvester **100** and the responsiveness of the controllable subsystems **216**.

By way of example, a generated predictive map **264** in the form of a predictive speed map can be used to control one or more subsystems **216**. For instance, the predictive speed map can include speed values georeferenced to locations within the field being harvested. The speed values from the predictive speed map can be extracted and used to control the propulsion subsystem **250**. By controlling the propulsion subsystem **250**, a feed rate of material moving through the agricultural harvester **100** can be controlled. Similarly, the header height can be controlled to take in more or less material, and, thus, the header height can also be controlled to control feed rate of material through the agricultural harvester **100**. In other examples, if the predictive map **264** maps weed height relative to positions in the field, control of the header height can be implemented. For example, if the values present in the predictive weed map indicate one or more areas having weed height with a first height amount, then header and reel controller **238** can control the header height so that the header is positioned above the first height amount of the weeds within the one or more areas having weeds at the first height amount when performing the harvesting operation. Thus, the header and reel controller **238** can be controlled using georeferenced values present in the predictive weed map to position the header to a height that is above the predicted height values of weeds obtained from the predictive weed map. Further, the header height can be changed automatically by the header and reel controller **238** as the agricultural harvester **100** proceeds through the field using georeferenced values obtained from the predictive weed map. The preceding example involving weed height and intensity using a predictive weed map is provided merely as an example. Consequently, a wide variety of other control signals can be generated using values obtained from a predictive weed map or other type of predictive map to control one or more of the controllable subsystems **216**.

At block **312**, a determination is made as to whether the harvesting operation has been completed. If harvesting is not completed, the processing advances to block **314** where in-situ sensor data from geographic position sensor **204** and in-situ sensors **208** (and perhaps other sensors) continue to be read.

In some examples, at block **316**, agricultural harvester **100** can also detect learning trigger criteria to perform machine learning on one or more of the predictive map **264**, predictive control zone map **265**, the model generated by predictive model generator **210**, the zones generated by control zone generator **213**, one or more control algorithms implemented by the controllers in the control system **214**, and other triggered learning.

The learning trigger criteria can include any of a wide variety of different criteria. Some examples of detecting trigger criteria are discussed with respect to blocks **318**, **320**, **321**, **322** and **324**. For instance, in some examples, triggered learning can involve recreation of a relationship used to generate a predictive model when a threshold amount of in-situ sensor data are obtained from in-situ sensors **208**. In such examples, receipt of an amount of in-situ sensor data from the in-situ sensors **208** that exceeds a threshold trigger or causes the predictive model generator **210** to generate a new predictive model that is used by predictive map generator **212**. Thus, as agricultural harvester **100** continues a harvesting operation, receipt of the threshold amount of in-situ sensor data from the in-situ sensors **208** triggers the creation of a new relationship represented by a predictive model generated by predictive model generator **210**. Further, new predictive map **264**, predictive control zone map **265**, or both can be regenerated using the new predictive model. Block **318** represents detecting a threshold amount of in-situ sensor data used to trigger creation of a new predictive model.

In other examples, the learning trigger criteria may be based on how much the in-situ sensor data from the in-situ sensors **208** are changing, such as over time or compared to previous values. For example, if variations within the in-situ sensor data (or the relationship between the in-situ sensor data and the information in prior information map **258**) are within a selected range or is less than a defined amount, or below a threshold value, then a new predictive model is not generated by the predictive model generator **210**. As a result, the predictive map generator **212** does not generate a new predictive map **264**, predictive control zone map **265**, or both. However, if variations within the in-situ sensor data are outside of the selected range, are greater than the defined amount, or are above the threshold value, for example, then the predictive model generator **210** generates a new predictive model using all or a portion of the newly received in-situ sensor data that the predictive map generator **212** uses to generate a new predictive map **264**. At block **320**, variations in the in-situ sensor data, such as a magnitude of an amount by which the data exceeds the selected range or a magnitude of the variation of the relationship between the in-situ sensor data and the information in the prior information map **258**, can be used as a trigger to cause generation of a new predictive model and predictive map. Keeping with the examples described above, the threshold, the range, and the defined amount can be set to default values; set by an operator or user interaction through a user interface; set by an automated system; or set in other ways.

Other learning trigger criteria can also be used. For instance, if predictive model generator **210** switches to a different prior information map (different from the originally selected prior information map **258**), then switching to the different prior information map may trigger re-learning by predictive model generator **210**, predictive map generator **212**, control zone generator **213**, control system **214**, or other items. In another example, transitioning of agricultural harvester **100** to a different topography or to a different control zone may be used as learning trigger criteria as well.

In some instances, operator **260** can also edit the predictive map **264** or predictive control zone map **265** or both. The edits can change a value on the predictive map **264**, change a size, shape, position, or existence of a control zone on predictive control zone map **265**, or both. Block **321** shows that edited information can be used as learning trigger criteria.

In some instances, it may also be that operator **260** observes that automated control of a controllable subsystem, is not what the operator desires. In such instances, the operator **260** may provide a manual adjustment to the controllable subsystem reflecting that the operator **260** desires the controllable subsystem to operate in a different way than is being commanded by control system **214**. Thus, manual alteration of a setting by the operator **260** can cause one or more of predictive model generator **210** to relearn a model, predictive map generator **212** to regenerate map **264**, control zone generator **213** to regenerate one or more control zones on predictive control zone map **265**, and control system **214** to relearn a control algorithm or to perform machine learning on one or more of the controller components **232** through **246** in control system **214** based upon the adjustment by the operator **260**, as shown in block **322**. Block **324** represents the use of other triggered learning criteria.

In other examples, relearning may be performed periodically or intermittently based, for example, upon a selected time interval such as a discrete time interval or a variable time interval, as indicated by block **326**.

If relearning is triggered, whether based upon learning trigger criteria or based upon passage of a time interval, as indicated by block **326**, then one or more of the predictive model generator **210**, predictive map generator **212**, control zone generator **213**, and control system **214** performs machine learning to generate a new predictive model, a new predictive map, a new control zone, and a new control algorithm, respectively, based upon the learning trigger criteria. The new predictive model, the new predictive map, and the new control algorithm are generated using any additional data that has been collected since the last learning operation was performed. Performing relearning is indicated by block **328**.

If the harvesting operation has been completed, operation moves from block **312** to block **330** where one or more of the predictive map **264**, predictive control zone map **265**, and predictive model generated by predictive model generator **210** are stored. The predictive map **264**, predictive control zone map **265**, and predictive model may be stored locally on data store **202** or sent to a remote system using communication system **206** for later use.

It will be noted that, while some examples herein describe predictive model generator **210** and predictive map generator **212** receiving a prior information map in generating a predictive model and a functional predictive map, respectively, in other examples, the predictive model generator **210** and predictive map generator **212** can receive, in generating a predictive model and a functional predictive map, respectively other types of maps, including predictive maps, such as a functional predictive map generated during the harvesting operation.

FIG. **4**A is a block diagram of a portion of the agricultural harvester **100** shown in FIG. **1**. Particularly, FIG. **4**A shows, among other things, examples of the predictive model generator **210** and the predictive map generator **212** in more detail. FIG. **4**A also illustrates information flow among the various components shown. The predictive model generator **210** receives prior information map **258**, which may be a vegetative index map **332**, a predictive yield map **333**, a biomass map **335**, a crop state map **337**, a topographic map **339**, a soil property map **341** or a seeding map **343** as a prior information map. In other example, predictive model generator **210** can receive various other maps **401**, such as other prior information maps or other predictive maps. Predictive model generator **210** also receives a geographic location **334**, or an indication of a geographic location, from geographic position sensor **204**. In-situ sensors **208** illustratively include machine speed sensor **146**, or a sensor **336** that senses an output from feed rate controller **236**, as well as a processing system **338**. The processing system **338** processes sensor data generated from machine speed sensor **146** or from sensor **336**, or both, to generate processed data, some examples of which are described below.

In some examples, sensor **336** may be a sensor, that generates a signal indicative of the control outputs from feed rate controller **236**. The control signals may be speed control signals or other control signals that are applied to controllable subsystems **216** to control feed rate of material through agricultural harvester **100**. Processing system **338** processes the signals obtained via the sensor **336** to generate processed data **340** identifying the speed of agricultural harvester **100**.

In some examples, raw or processed data from in-situ sensor(s) **208** may be presented to operator **260** via operator interface mechanism **218**. Operator **260** may be onboard the agricultural harvester **100** or at a remote location.

The present discussion proceeds with respect to an example in which in-situ sensor **208** is machine speed sensor **146**. It will be appreciated that this is just one example, and the sensors mentioned above, as other examples of in-situ sensor **208** from which machine speed can be derived, are contemplated herein as well. As shown in FIG. **4**A, the example predictive model generator **210** includes one or more of a vegetative index (VI) value-to-speed model generator **342**, a biomass-to-speed model generator **344**, topography-to-speed model generator **345**, yield-to-speed model generator **347**, crop state-to-speed model generator **349**, soil property-to-speed model generator **351** and a seeding characteristic-to-speed model generator **346**. In other examples, the predictive model generator **210** may include additional, fewer, or different components than those shown in the example of FIG. **4**A. Consequently, in some examples, the predictive model generator **210** may include other items **348** as well, which may include other types of predictive model generators to generate other types of models.

Model generator **342** identifies a relationship between machine speed detected in processed data **340**, at a geographic location corresponding to where the processed data **340** were obtained, and one or more vegetative index values from the vegetative index map **332** corresponding to the same location in the field where the speed characteristic was detected. Based on this relationship established by model generator **342**, model generator **342** generates a predictive speed model. The predictive speed model is used by speed map generator **352** to predict target or expected machine speed values at different locations in the field based upon the georeferenced vegetative index value contained in the vegetative index map **332** at the same locations in the field.

Model generator **344** identifies a relationship between machine speed represented in the processed data **340**, at a geographic location corresponding to the processed data **340**, and the biomass value at the same geographic location. Again, the biomass value is the georeferenced value contained in the biomass map **335**. Model generator **344** then generates a predictive speed model that is used by speed map generator **352** to predict the target machine speed at a location in the field based upon the biomass value for that location in the field.

Model generator **345** identifies a relationship between machine speed represented in the processed data **340**, at a geographic location corresponding to the processed data **340**, and the topographic characteristic value at the same geographic location. Again, the topographic characteristic value is the georeferenced value contained in the topographic map **339**. Model generator **345** then generates a predictive speed model that is used by speed map generator **352** to predict the target or expected machine speed at a location in the field based upon the topographic characteristic value for that location in the field.

Model generator **346** identifies a relationship between the machine speed identified by processed data **340** at a particular location in the field and the seeding characteristic value from the seeding characteristic map **343** at that same location. Model generator **346** generates a predictive speed model that is used by speed map generator **352** to predict target or expected machine speed values at a particular location in the field based upon the seeding characteristic value at that location in the field.

Model generator **347** identifies a relationship between machine speed represented in the processed data **340**, at a geographic location corresponding to the processed data **340**, and the yield value at the same geographic location. Again, the yield value is the georeferenced value contained in the predictive yield map **333**. Model generator **347** then generates a predictive speed model that is used by speed map generator **352** to predict the target or expected machine speed at a location in the field based upon the yield value for that location in the field.

Model generator **348** identifies a relationship between machine speed represented in the processed data **340**, at a geographic location corresponding to the processed data **340**, and the crop state value at the same geographic location. Again, the crop state value is the georeferenced value contained in the crop state map **337**. Model generator **348** then generates a predictive speed model that is used by speed map generator **352** to predict the target or expected machine speed at a location in the field based upon the topographic characteristic value for that location in the field.

Model generator **351** identifies a relationship between machine speed represented in the processed data **340**, at a geographic location corresponding to the processed data **340**, and the soil property value at the same geographic location. Again, the soil property value is the georeferenced value contained in the soil property map **341**. Model generator **351** then generates a predictive speed model that is used by speed map generator **352** to predict the target or expected machine speed at a location in the field based upon the topographic characteristic value for that location in the field.

In light of the above, the predictive model generator **210** is operable to produce a plurality of predictive speed models, such as one or more of the predictive speed models generated by model generators **342**, **344**, **345**, **346**, **347**, **348** and **351**. In another example, two or more of the predictive speed models described above may be combined into a single predictive speed model that predicts target machine speed based on two or more of the vegetative index value, the biomass value, the topography, the yield, the seeding characteristic, the crop state, or the soil property, at different locations in the field. Any of these speed models, or combinations thereof, are represented collectively by predictive model **350** in FIG. **4**A.

The predictive model **350** is provided to predictive map generator **212**. In the example of FIG. **4**A, predictive map generator **212** includes a speed map generator **352**. In other examples, the predictive map generator **212** may include additional, fewer, or different map generators. Thus, in some examples, the predictive map generator **212** may include other items **358** which may include other types of map generators to generate speed maps. Speed map generator **352** receives the predictive model **350**, which predicts target machine speed based upon a value from one or more prior information maps **258**, along with the one or more prior information maps **258**, and generates a predictive map that predicts the target machine speed at different locations in the field.

Predictive map generator **212** outputs one or more functional predictive speed maps **360** that are predictive of one or more of target machine speed. The functional predictive speed map **360** predicts the target machine speed at different locations in a field. The functional predictive speed maps **360** may be provided to control zone generator **213**, control system **214**, or both. Control zone generator **213** generates control zones and incorporates those control zones into the functional predictive map, i.e., predictive map **360**, to produce predictive control zone map **265**. One or both of predictive map **264** and predictive control zone map **265** may be provided to control system **214**, which generates control signals to control one or more of the controllable subsystems **216**, such as propulsion subsystem **250** based upon the predictive map **264**, predictive control zone map **265**, or both.

FIG. **4**B is a block diagram of a portion of the agricultural harvester **100** shown in FIG. **1**. Particularly, FIG. **4**B shows, among other things, examples of the predictive model generator **210** and the predictive map generator **212** in more detail. FIG. **4**B also illustrates information flow among the various components shown. The predictive model generator **210** receives a topographic map **339**, as a prior information map. Topographic map **332** includes georeferenced topographic characteristic values. The predictive model generator **210** also receives a predictive speed map, such as functional predictive speed map **360**. The functional predictive speed map **360** includes georeferenced predictive speed values. In other examples, predictive model generator **210** can receive other maps **401**, such as other prior information maps or other predictive maps, such as other predictive speed maps generated in ways other than the way in which functional predictive speed map **360** was generated, for example.

Generator **210** is also receiving a geographic location indicator **334** from geographic position sensor **204**. In-situ sensors **208** illustratively include a cut height sensor, such as cut height sensor **1336**, a header height sensor, such as header height sensor **1337**, as well as a processing system **1338**. Cut height sensor **1336** detects characteristics indicative of a height at which vegetation on the field is cut. In some examples, cut height sensor **1336** is an optical sensor that detects cut vegetation material and generates sensor data indicative a height at which the vegetation material was cut. Header height sensor **1337** can sense a variety of characteristics, such as a variety of characteristics indicative of header height or header position (such as pitch or roll) and generates a sensor signal indicative of header height. In some examples, the output of header height sensor **1337** can also be indicative of a cut height. In some instances, cut height sensor **1336** or header height sensor **1337**, or both, may be located on board the agricultural harvester **100**. The processing system **1338** processes sensor data generated from cut height sensor **1336** or header height sensor **1337**, or both, to generate processed sensor data **1340**, such as processed sensor data indicative of cut height, cut height variability, header height, or header height variability, some examples of which are described below.

The present discussion proceeds with respect to an example in which cut height sensor **1336** senses cut height characteristics and header height sensor **1337** senses a height of a header on agricultural harvester **100** above a surface of the field. As shown in FIG. **4**B, the example predictive model generator **210** includes one or more of a speed and topographic characteristic-to-cut height model generator **1342**, a speed-to-cut height model generator **1343**, a speed-to-cut height variability model generator **1345**, a speed and topographic characteristic-to-cut height variability model generator **1344**, a topographic characteristic-to-cut height model generator, and a topographic characteristic-to-cut height variability model generator **1347**. In other examples, the predictive model generator **210** may include additional, fewer, or different components than those shown in the example of FIG. **4**B. Consequently, in some examples, the predictive model generator **210** may include other items **348** as well, which may include other types of predictive model generators to generate other types of cut height characteristic models. For example, predictive model generator **210** may include specific topographic characteristic model generators, for instance, a slope-to-cut height model generator or a slope-to-cut height variability model generator. Slope can also include a variability of slope.

Speed and topographic characteristic-to-cut height model generator **1342** identifies a relationship between cut height, at a geographic location corresponding to where cut height sensor **1336** sensed the cut height characteristic indicative of the height at which vegetation on the field was cut or where header height sensor **1337** sensed the header height, or both, and speed values from the predictive speed map **360** and topographic characteristic values, such as one or more slope values, from the topographic map **339** corresponding to the same location in the field where the detected cut height corresponds. Based on this relationship established by speed and topographic characteristic-to-cut height model generator **1342**, speed and topographic characteristic-to-cut height model generator **1342** generates a predictive cut height characteristic model. The predictive cut height characteristic model is used by predictive map generator **212** to predict cut height at different locations in the field based upon the georeferenced speed values and georeferenced topographic characteristic values, such as slope values, contained in the predictive speed map **360** and topographic map **339**, respectively, at the same locations in the field. In some examples, the speed values can be derived from another map other than predictive speed map **360**, such as other map **401**, which may include other predictive speed maps or other prior information maps.

Speed and topographic characteristic-to-cut height variability model generator **1344** identifies a relationship between variation in cut height, at a geographic location corresponding to where cut height sensor **1336** sensed the variable cut heights or where header height sensor **1337** sensed the variable header heights, and speed values from the predictive speed map **360** and topographic characteristic values, such as one or more slope values, from the topographic map **339** corresponding to the same location(s) in the field where the detected variable header height or detected variable cut height corresponds, or both. Based on this relationship established by speed and topographic characteristic-to-cut height variability model generator **1344**, speed and topographic characteristic-to-cut height variability height model generator **1344** generates a predictive cut height characteristic model. The predictive cut height characteristic model **1350** is used by predictive map generator **212** to predict cut height variability at different locations in the field based upon the georeferenced speed values contained in the predictive speed map and the georeferenced topographic characteristic values, such as slope values, contained in the topographic map **339** at the same locations in the field. In some examples, the speed values can be derived from another map other than predictive speed map **360**, such as other map **401**, which may include other predictive speed maps or other prior information maps.

Speed-to-cut height model generator **1343** identifies a relationship between cut height represented in the processed data **1340**, at a geographic location corresponding to the processed data **1340**, and the speed value at the same geographic location. The speed value is the georeferenced value contained in the predictive speed map **360**. Model generator **1343** then generates a predictive cut height characteristic model that is used by predictive cut height map generator **1352** to predict the cut height at a location in the field based upon the speed value for that location in the field.

Speed-to-cut height variability model generator **1345** identifies a relationship between cut height variability represented in the processed data **1340**, at a geographic location corresponding to the processed data **1340**, and the speed value at the same geographic location. The speed value is the georeferenced value contained in the predictive speed map **360**. Model generator **1345** then generates a predictive cut height characteristic model that is used by predictive cut height variability map generator **1354** to predict the cut height variability at a location in the field based upon the speed value for that location in the field.

Topographic characteristic-to-cut height model generator **1346** identifies a relationship between cut height represented in the processed data **1340**, at a geographic location corresponding to the processed data **1340**, and the topographic characteristic value at the same geographic location. The topographic characteristic value is the georeferenced value contained in the topographic map **339**. Model generator **1346** then generates a predictive cut height characteristic model that is used by predictive cut height map generator **1352** to predict the cut height at a location in the field based upon the topographic characteristic value for that location in the field.

Topographic characteristic-to-cut height variability model generator **1347** identifies a relationship between cut height variability represented in the processed data **1340**, at a geographic location corresponding to the processed data **1340**, and the topographic characteristic value at the same geographic location. The topographic characteristic value is the georeferenced value contained in the topographic map **339**. Model generator **1347** then generates a predictive cut height characteristic model that is used by predictive cut height variability map generator **1354** to predict the cut height variability at a location in the field based upon the topographic characteristic value for that location in the field.

In light of the above, the predictive model generator **210** is operable to produce a plurality of predictive cut height characteristic models, such as one or more of the predictive cut height characteristic models generated by model generators **1342**, **1343** **1344**, **1345**, **1346**, **1347** and **1348**. In another example, two or more of the predictive cut height characteristic models described above may be combined into a single predictive cut height characteristic model that predicts cut height and cut height variability at different locations in the field based upon the different values, such as detected cut height, detected cut height variability, detected header height, and detected header height variability. Any of these cut height characteristic models, or combinations thereof, are represented collectively by cut height characteristic model **1350** in FIG. **4**B.

The predictive cut height characteristic model **1350** is provided to predictive map generator **212**. In the example of FIG. **4**B, predictive map generator **212** includes a cut height map generator **1352** and a cut height variability map generator **1354**. In other examples, the predictive map generator **212** may include additional, fewer, or different map generators. Thus, in some examples, the predictive map generator **212** may include other items **1358**, such as other types of map generators to generate cut height maps. For example, predictive map generator **212** may include a header height map generator or a header height variability map generator, or both.

Cut height map generator **1352** receives the predictive cut height characteristic model **1350** that predicts cut height based upon speed values or topographic characteristic values, or both, and based upon in-situ sensor data indicative of cut height, such as sensor data from cut height sensor **1336** or header height sensor **1337**, or both. Using the predictive cut height characteristic model **1350** and one or more of the received maps, the cut height map generator **1352** generates a predictive map that maps the predicted cut height at different locations in the field.

Cut height variability map generator **1354** receives the predictive cut height characteristic model **1350** that predicts cut height variability based upon speed values or topographic characteristic values, or both, and based upon in-situ sensor data indicative of cut height variability, such as sensor data from cut height sensor **1336** or header height sensor **1337**, or both. Using the predictive cut height characteristic model **1350** and one or more of the received maps, the cut height variability map generator **1354** generates a predictive map that maps the predicted cut height variability at different locations in the field.

Predictive map generator **212** outputs one or more functional predictive cut height characteristic maps **1360** that are predictive of one or more of cut height or cut height variability. Each of the predictive cut height characteristic maps **1360** predicts the cut height or cut height variability at different locations in a field. Each of the generated predictive cut height characteristic maps **1360** may be provided to control zone generator **213**, control system **214**, or both. Control zone generator **213** generates control zones and incorporates those control zones into the functional predictive map, i.e., functional predictive map **1360**, to provide functional predictive map **1360** with control zones. Functional predictive map **1360** (with or without control zones) may be provided to control system **214**, which generates control signals to control one or more of the controllable subsystems **216** based upon the functional predictive map **1360** (with or without control zones).

FIG. **5** is a flow diagram of an example of operation of predictive model generator **210** and predictive map generator **212** in generating the predictive cut height characteristic model **1350** and the functional predictive cut height characteristic map **1360**. At block **362**, predictive model generator **210** and predictive map generator **212** receives one or more of a predictive speed map, such as functional predictive speed map **360**; a topographic map, such as topographic map **339**; or some other map **401**. At block **364**, processing system **1338** receives one or more sensor signals from in-situ sensors **208**, such as cut height sensor **1336** or header height sensor **1337**, or both. In other examples, in-situ sensor **208** may be another type of sensor, as indicated by block **370**. For example, in-situ sensor **208** may be another type of sensor that provides an indication of cut height, cut height variability, header height, or header height variability.

At block **372**, processing system **1338** processes the one or more received sensor signals to generate data indicative of cut height characteristics. As indicated by block **374**, the cut height characteristics may be cut height. As indicated by block **376**, the cut height characteristic may be cut height variability. As indicated by block **380**, the sensor data can be indicative of other characteristics, such as header height or header height variability. As discussed previously herein, header height and header height variability can be indicative of cut height and cut height variability.

At block **382**, predictive model generator **210** also obtains the geographic location corresponding to the sensor data. For instance, the predictive model generator **210** can obtain the geographic position from geographic position sensor **204** and determine, based upon machine delays, machine speed, etc., a precise geographic location or area where the sensor data **340** was captured or derived.

At block **384**, predictive model generator **210** generates one or more predictive models, such as one or more of the cut height characteristic models generated by model generators **1342**, **1343**, **1344**, **1345**, **1346**, **1347** or **1348**, which are represented collectively by cut height characteristic model **1350**.

At block **386**, the predictive model, such as predictive cut height characteristic model **1350**, is provided to predictive map generator **212**. The predictive map generator **212** generates a predictive cut height characteristic map **1360** that maps a predicted cut height characteristic based on a predictive speed map, such as predictive speed map **360** or a topographic map **339**, or both, and predictive cut height characteristic model **1350**. For instance, in some examples, the predictive cut height characteristic map **1360** maps predicted cut height or predicted cut height variability at various locations across the field. Further, the predictive cut height characteristic map **1360** can be generated during the course of an agricultural operation. Thus, as an agricultural harvester is moving through a field performing an agricultural operation, the predictive cut height characteristic map **1360** is generated as the agricultural operation is being performed.

At block **394**, predictive map generator **212** outputs the predictive cut height characteristic map **1360**. At block **391**, predictive map generator **212** outputs the predictive cut height characteristic map **1360** for presentation to and possible interaction by operator **260**. At block **393**, predictive map generator **212** may configure the predictive cut height characteristic map **1360** for consumption by control system **214**. At block **395**, predictive map generator **212** can also provide the predictive cut height characteristic map **1360** to control zone generator **213** for generation and incorporation of control zones. At block **397**, predictive map generator **212** configures the predictive cut height characteristic map **1360** in other ways as well. The predictive cut height characteristic map **1360** (with or without the control zones) is provided to control system **214**. At block **396**, control system **214** generates control signals to control the controllable subsystems **216** based upon the functional predictive cut height characteristic map **1360**.

In an example in which control system **214** receives a functional predictive map or a functional predictive map with control zones added, the path planning controller **234** controls steering subsystem **252** to steer agricultural harvester **100**. In another example in which control system **214** receives afunctional predictive map or a functional predictive map with control zones added, the residue system controller **244** controls residue subsystem **138**. In another example in which control system **214** receives a functional predictive map or a functional predictive map with control zones added, the settings controller **232** controls thresher settings of thresher **110**. In another example in which control system **214** receives a functional predictive map or a functional predictive map with control zones added, the settings controller **232** or another controller **246** controls material handling subsystem **125**. In another example in which control system **214** receives a functional predictive map or a functional predictive map with control zones added, the settings controller **232** controls crop cleaning subsystem **118**. In another example in which control system **214** receives a functional predictive map or a functional predictive map with control zones added, the machine cleaning controller **245** controls machine cleaning subsystem **254** on agricultural harvester **100**. In another example in which control system **214** receives a functional predictive map or a functional predictive map with control zones added, the communication system controller **229** controls communication system **206**. In another example in which control system **214** receives a functional predictive map or a functional predictive map with control zones added, the operator interface controller **231** controls operator interface mechanisms **218** on agricultural harvester **100**. In another example in which control system **214** receives the functional predictive map or the functional predictive map with control zones added, the deck plate position controller **242** controls machine/header actuators **248** to control a deck plate on agricultural harvester **100**. In another example in which control system **214** receives the functional predictive map or the functional predictive map with control zones added, the draper belt controller **240** controls machine/header actuators **248** to control a draper belt on agricultural harvester **100**. In another example in which control system **214** receives the functional predictive map or the functional predictive map with control zones added, the other controllers **246** control other controllable subsystems **256** on agricultural harvester **100**.

In one example, control system **214** may receive a functional predictive map or a functional predictive map with control zones added, and header/reel controller **238** can control header or other machine actuators **248** to control a height, tilt, or roll of header **102** based upon the functional predictive map (with or without control zones). For instance, header/reel controller **238** can control header or other machine actuators **248** to adjust a height of header **102** above the surface of the field. In another example, header/reel controller **238** can control header or other machine actuators **248** to adjust a tilt of header, such as a tilt of header **102** from fore-to-aft (tilt can also referred to as a pitch). In another example, header/reel controller **238** can control header other machine actuators **238** to adjust a roll of header, such as a roll of header **102** from side-to-side, that is, across the width of header.

In one example, control system **214**, or an operator of the agricultural harvester may receive a functional predictive map or a functional predictive map with control zones added and based thereupon adjust one or more header settings, such as header position settings (such as a header height setting, a header pitch setting, or a header roll setting), a header sensitivity setting which controls the responsiveness of the agricultural harvester in responding to header height errors, or a ground pressure setting that controls the amount of float force exerted on the header by one or more actuators, such as hydraulic cylinders.

It can thus be seen that the present system receives a map that maps a characteristic value such as a topographic characteristic value or a predictive speed value to different locations in a field. The present system also uses one or more in-situ sensors that sense in-situ sensor data that is indicative of a cut height characteristic, such as cut height or cut height variability, and generates a model that models a relationship between the characteristic sensed using the in-situ sensor, or a related characteristic, and the characteristics mapped in the received map. Thus, the present system generates a functional predictive map using a model, in-situ data, and a map, and may configure the generated functional predictive map for consumption by a control system, for presentation to a local or remote operator or other user, or both. For example, the control system may use the map to control one or more systems of a combine harvester.

FIG. **6**A is a block diagram of an example portion of the agricultural harvester **100** shown in FIG. **1**. Particularly, FIG. **6**A shows, among other things, examples of predictive model generator **210** and predictive map generator **212**. In the illustrated example, the prior information map **258** is a prior operation map **400**. Prior operation map **400** may include cut height characteristic values at various locations in the field from a prior operation on the field. For example, prior operation map **400** may be a historical cut height characteristic map, generated during a harvesting operation in a previous harvesting seasons, that includes cut height characteristic values at various locations, and may include contextual information such as header settings, speed of operation, as well as various other machine settings utilized during the previous operation. FIG. **6**A also shows that predictive model generator **210** and predictive map generator **212** can receive, alternatively or in addition to prior information map **258**, functional predictive cut height characteristic map, such as functional predictive cut height characteristic map **1360**. Functional predictive cut height characteristic map **1360** can be used similarly as prior information map **258** in that model generator **210** models a relationship between information provided by functional predictive cut height characteristic map **1360** and characteristics sensed by in-situ sensors **208**. Map generator **212** can, thus, use the model to generate a functional predictive map that predicts the characteristics sensed by the in-situ sensors **208**, or a characteristic related to the sensed characteristic, at different locations in the field based upon one or more of the values in the functional predictive cut height characteristic map **1360** at those locations in the field and based on the predictive model. As illustrated in FIG. **6**A, predictive model generator **210** and predictive map generator **212** can also receive other maps **401**, for instance other prior information maps or other predictive maps, such as other predictive cut height characteristic maps generated in other ways than functional predictive cut height characteristic map **1360**.

Also, in the example shown in FIG. **6**A, in-situ sensor **208** can include one or more of an agricultural characteristic sensor **402**, operator input sensor **404**, and a processing system **406**. In-situ sensors **208** can include other sensors **408** as well.

Agricultural characteristic sensor **402** senses values indicative of agricultural characteristics. Operator input sensor **404** senses various operator inputs. The inputs can be setting inputs for controlling the settings on agricultural harvester **100** or other control inputs, such as steering inputs and other inputs. Thus, when operator **260** changes a setting or provides a commanded input through an operator interface mechanism **218**, such an input is detected by operator input sensor **404**, which provides a sensor signal indicative of that sensed operator input. In one example, the input can be header setting inputs (or other setting inputs related to control of the header), such as header sensitivity setting inputs, header position inputs (such as header height setting inputs, header pitch setting inputs, or header roll setting inputs), header ground pressure setting inputs, as well as various other header setting inputs.

Processing system **406** may receive the sensor signals from one or more of agricultural characteristic sensor **402** and operator input sensor **404** and generate an output indicative of the sensed variable. For instance, processing system **406** may receive a sensor output from agricultural characteristic sensor **402** and generate an output indicative of an agricultural characteristic. Processing system **406** may also receive an input from operator input sensor **404** and generate an output indicative of the sensed operator input.

Predictive model generator **210** may include cut height characteristic-to-agricultural characteristic model generator **410** and cut height characteristic-to-command model generator **414**. In other examples, predictive model generator **210** can include additional, fewer, or other model generators **415**. For example, predictive model generator **210** may include specific cut height characteristic model generators, such as a cut height-to-agricultural characteristic model generator, a cut height variability-to-agricultural characteristic model generator, a cut height-to-command model generator, or a cut height variability-to-command model generator. Predictive model generator **210** may receive a geographic location indicator **334** from geographic position sensor **204** and generate a predictive model **426** that models a relationship between the information in one or more of the prior information maps **258** or the information in functional predictive cut height characteristic map **1360** and one or more of: the agricultural characteristic sensed by agricultural characteristic sensor **402** and operator input commands sensed by operator input sensor **404**.

Cut height characteristic-to-agricultural characteristic model generator **410** generates a relationship between cut height characteristic values (such as cut height characteristics provided on predictive cut height characteristic map **1360**, prior operation map **400**, or other map **401**) and the agricultural characteristic sensed by agricultural characteristic sensor **402**. Cut height characteristic-to-agricultural characteristic model generator **410** generates a predictive model **426** that corresponds to this relationship.

Cut height characteristic-to-operator command model generator **414** generates a model that models the relationship between a cut height characteristic as reflected on predictive cut height characteristic map **1360**, prior operation map **400**, or other map **401** and operator input commands that are sensed by operator input sensor **404**. Cut height characteristic-to-operator command model generator **414** generates a predictive model **426** that corresponds to this relationship.

Other model generators **415** may include, for example, specific cut height characteristic model generators, such as a cut height-to-agricultural characteristic model generator, a cut height variability-to-agricultural characteristic model generator, a cut height-to-command model generator, or a cut height variability-to-command model generator.

Predictive model **426** generated by the predictive model generator **210** can include one or more of the predictive models that may be generated by cut height characteristic-to-agricultural characteristic model generator **410** and cut height characteristic-to-operator command model generator **414**, and other model generators that may be included as part of other items **415**.

In the example of FIG. **6**A, predictive map generator **212** includes predictive agricultural characteristic map generator **416** and a predictive operator command map generator **422**. In other examples, predictive map generator **212** can include additional, fewer, or other map generators **424**.

Predictive agricultural characteristic map generator **416** receives a predictive model **426** that models the relationship between a cut height characteristic and an agricultural characteristic sensed by agricultural characteristic **402** (such as a predictive model generated by cut height characteristic-to-agricultural characteristic model generator **410**), and one or more of the prior information maps **258** or functional predictive cut height characteristic map **1360**, or other maps **401**. Predictive agricultural characteristic map generator **416** generates a functional predictive agricultural characteristic map **427** that predicts agricultural characteristic values (or the agricultural characteristics of which the values are indicative) at different locations in the field based upon one or more of the cut height characteristic values in one or more of the prior information maps **258** or the functional predictive cut height characteristic map **1360**, or other map **401** at those locations in the field and based on predictive model **426**.

Predictive operator command map generator **422** receives a predictive model **426** that models the relationship between the cut height characteristic and operator command inputs detected by operator input sensor **404** (such as a predictive model generated by cut height characteristic-to-command model generator **414**), and one or more of the prior information maps **258** or the functional predictive cut height characteristic map **1360**, or other maps **401**. Predictive operator command map generator **422** generates a functional predictive operator command map **440** that predicts operator command inputs at different locations in the field based upon one or more of the cut height characteristic values from the prior information map **258** or the functional predictive cut height characteristic map **1360**, or other map **401** at those locations in the field and based on predictive model **426**.

Predictive map generator **212** outputs one or more of the functional predictive maps **427** and **440**. Each of the functional predictive maps **427** and **440** may be provided to control zone generator **213**, control system **214**, or both. Control zone generator **213** generates and incorporates control zones to provide a functional predictive map **427** with control zones and a functional predictive map **440** with control zones. Any or all of functional predictive maps **427** and **440** (with or without control zones) may be provided to control system **214**, which generates control signals to control one or more of the controllable subsystems **216** based upon one or all of the functional predictive maps **427** and **440** (with or without control zones). Any or all of the maps **427** and **440** (with or without control zones) may be presented to operator **260** or another user.

FIG. **6**B is a block diagram showing some examples of real-time (in-situ) sensors **208**. Some of the sensors shown in FIG. **6**B, or different combinations of them, may have both a sensor **402** and a processing system **406**, while others may act as sensor **402** described with respect to FIGS. **6**A and **7** where the processing system **406** is separate. Some of the possible in-situ sensors **208** shown in FIG. **6**B are shown and described above with respect to previous FIGS. and are similarly numbered. FIG. **6**B shows that in-situ sensors **208** can include operator input sensors **980**, machine sensors **982**, harvested material property sensors **984**, field and soil property sensors **985**, environmental characteristic sensors **987**, and they may include a wide variety of other sensors **226**. Operator input sensors **980** may be sensors that sense operator inputs through operator interface mechanisms **218**. Therefore, operator input sensors **980** may sense user movement of linkages, joysticks, a steering wheel, buttons, dials, or pedals. Operator input sensors **980** can also sense user interactions with other operator input mechanisms, such as with a touch sensitive screen, with a microphone where speech recognition is utilized, or any of a wide variety of other operator input mechanisms.

Machine sensors **982** may sense different characteristics of agricultural harvester **100**. For instance, as discussed above, machine sensors **982** may include machine speed sensors **146**, separator loss sensor **148**, clean grain camera **150**, forward looking image capture mechanism **151**, loss sensors **152** or geographic position sensor **204**, examples of which are described above. Machine sensors **982** can also include machine setting sensors **991** that sense machine settings. Some examples of machine settings were described above with respect to FIG. **1**. Front-end equipment (e.g., header) position sensor **993** can sense the position of the header **102**, reel **164**, cutter **104**, or other front-end equipment relative to the frame of agricultural harvester **100**. For instance, sensors **993** may sense the height of header **102** above the ground. Machine sensors **982** can also include front-end equipment (e.g., header) orientation sensors **995**. Sensors **995** may sense the orientation of header **102** relative to agricultural harvester **100**, or relative to the ground. Machine sensors **982** may include stability sensors **997**. Stability sensors **997** sense oscillation or bouncing motion (and amplitude) of agricultural harvester **100**. Machine sensors **982** may also include residue setting sensors **999** that are configured to sense whether agricultural harvester **100** is configured to chop the residue, produce a windrow, or deal with the residue in another way. Machine sensors **982** may include cleaning shoe fan speed sensor **951** that senses the speed of cleaning fan **120**. Machine sensors **982** may include concave clearance sensors **953** that sense the clearance between the rotor **112** and concaves **114** on agricultural harvester **100**. Machine sensors **982** may include chaffer clearance sensors **955** that sense the size of openings in chaffer **122**. The machine sensors **982** may include threshing rotor speed sensor **957** that senses a rotor speed of rotor **112**. Machine sensors **982** may include rotor drive force sensor **959** that senses the force used to drive rotor **112**. Machine sensors **982** may include sieve clearance sensor **961** that senses the size of openings in sieve **124**. The machine sensors **982** may include MOG moisture sensor **963** that senses a moisture level of the MOG passing through agricultural harvester **100**. Machine sensors **982** may include machine orientation sensor **965** that senses the orientation of agricultural harvester **100**. Machine sensors **982** may include material feed rate sensors **967** that sense the feed rate of material as the material travels through feeder house **106**, clean grain elevator **130**, or elsewhere in agricultural harvester **100**. Machine sensors **982** can include biomass sensors **969** that sense the biomass traveling through feeder house **106**, through separator **116**, or elsewhere in agricultural harvester **100**. The machine sensors **982** may include fuel consumption sensor **971** that senses a rate of fuel consumption over time of agricultural harvester **100**. Machine sensors **982** may include power utilization sensor **973** that senses power utilization in agricultural harvester **100**, such as which subsystems are utilizing power, or the rate at which subsystems are utilizing power, or the distribution of power among the subsystems in agricultural harvester **100**. Machine sensors **982** may include tire pressure sensors **977** that sense the inflation pressure in tires **144** of agricultural harvester **100**. Machine sensor **982** may include a wide variety of other machine performance sensors, or machine characteristic sensors, indicated by block **975**. The machine performance sensors and machine characteristic sensors **975** may sense machine performance or characteristics of agricultural harvester **100**.

Harvested material property sensors **984** may sense characteristics of the severed crop material as the crop material is being processed by agricultural harvester **100**. The crop properties may include such things as crop type, crop moisture, grain quality (such as broken grain), MOG levels, grain constituents such as starches and protein, MOG moisture, and other crop material properties. Other sensors could sense straw "toughness", adhesion of corn to ears, and other characteristics that might be beneficially used to control processing for better grain capture, reduced grain damage, reduced power consumption, reduced grain loss, etc.

Field and soil property sensors **985** may sense characteristics of the field and soil. The field and soil properties may include soil moisture, soil compactness, the presence and location of standing water, soil type, and other soil and field characteristics.

Environmental characteristic sensors **987** may sense one or more environmental characteristics. The environmental characteristics may include such things as wind direction and wind speed, precipitation, fog, dust level or other obscurants, or other environmental characteristics.

FIG. **7** shows a flow diagram illustrating one example of the operation of predictive model generator **210** and predictive map generator **212** in generating one or more predictive models **426** and one or more functional predictive maps **427** and **440**. At block **442**, predictive model generator **210** and predictive map generator **212** receive a map. The map received by predictive model generator **210** or predictive map generator **212** in generating one or more predictive models **426** and one or more functional predictive maps **427** and **440** may be prior information map **258**, such as a prior operation map **400** created using data obtained during a prior operation in a field. The map received by predictive model generator **210** or predictive map generator **212** in generating one or more predictive models **426** and one or more functional predictive maps **427** and **440** may be functional predictive cut height characteristic map **1360**. Other maps can be received as well as indicated by block **401**, such as other prior information maps or other predictive maps, for instance, other predictive cut height characteristic maps.

At block **444**, predictive model generator **210** receives a sensor signal containing sensor data from an in-situ sensor **208**. The in-situ sensor can be one or more of an agricultural characteristic sensor **402** and an operator input sensor **404**. Agricultural characteristic sensor **402** senses an agricultural characteristic. Operator input sensor **404** senses an operator input command. Predictive model generator **210** can receive other in-situ sensor inputs as well, as indicated by block **408**.

At block **454**, processing system **406** processes the data contained in the sensor signal or signals received from the in-situ sensor or sensors **208** to obtain processed data **409**, shown in FIG. **6**A. The data contained in the sensor signal or signals can be in a raw format that is processed to receive processed data **409**. For example, a temperature sensor signal includes electrical resistance data, this electrical resistance data can be processed into temperature data. In other examples, processing may comprise digitizing, encoding, formatting, scaling, filtering, or classifying data. The processed data **409** may be indicative of one or more of an agricultural characteristic or an operator input command. The processed data **409** is provided to predictive model generator **210**.

Returning to FIG. **7**, at block **456**, predictive model generator **210** also receives a geographic location **334** from geographic position sensor **204**, as shown in FIG. **6**A. The geographic location **334** may be correlated to the geographic location from which the sensed variable or variables, sensed by in-situ sensors **208**, were taken. For instance, the predictive model generator **210** can obtain the geographic location **334** from geographic position sensor **204** and determine, based upon machine delays, machine speed, etc., a precise geographic location from which the processed data **409** was derived.

At block **458**, predictive model generator **210** generates one or more predictive models **426** that model a relationship between a mapped value in a received map and a characteristic represented in the processed data **409**. For example, in some instances, the mapped value in a received map may be a cut height characteristic, such as cut height or cut height variability, and the predictive model generator **210** generates a predictive model using the mapped value of a received map and a characteristic sensed by in-situ sensors **208**, as represented in the processed data **409**, or a related characteristic, such as a characteristic that correlates to the characteristic sensed by in-situ sensors **208**.

The one or more predictive models **426** are provided to predictive map generator **212**. At block **466**, predictive map generator **212** generates one or more functional predictive maps. The functional predictive maps may be functional predictive agricultural characteristic map **427** and a functional predictive operator command map **440**, or any combination of these maps. Functional predictive agricultural characteristic map **427** predicts agricultural characteristic values (or agricultural characteristics indicated by the values) at different locations in the field. Functional predictive operator command map **440** predicts desired or likely operator command inputs at different locations in the field. Further, one or more of the functional predictive maps **427** and **440** can be generated during the course of an agricultural operation. Thus, as agricultural harvester **100** is moving through a field performing an agricultural operation, the one or more predictive maps **427** and **440** are generated as the agricultural operation is being performed.

At block **468**, predictive map generator **212** outputs the one or more functional predictive maps **427** and **440**. At block **470**, predictive map generator **212** may configure the map for presentation to and possible interaction by an operator **260** or another user. At block **472**, predictive map generator **212** may configure the map for consumption by control system **214**. At block **474**, predictive map generator **212** can provide the one or more predictive maps **427** and **440** to control zone generator **213** for generation of control zones. At block **476**, predictive map generator **212** configures the one or predictive maps **427** and **440** in other ways. In an example in which the one or more functional predictive maps **427** and **440** are provided to control zone generator **213**, the one or more functional predictive maps **427** and **440**, with the control zones included therewith, represented by corresponding maps **265**, described above, may be presented to operator **260** or another user or provided to control system **214** as well.

At block **478**, control system **214** then generates control signals to control the controllable subsystems based upon the one or more functional predictive maps **427** and **440** (or the functional predictive maps **427** and **440** having control zones) as well as an input from the geographic position sensor **204**.

In an example in which control system **214** receives a functional predictive map or a functional predictive map with control zones added, the path planning controller **234** controls steering subsystem **252** to steer agricultural harvester **100**. In another example in which control system **214** receives afunctional predictive map or a functional predictive map with control zones added, the residue system controller **244** controls residue subsystem **138**. In another example in which control system **214** receives a functional predictive map or a functional predictive map with control zones added, the settings controller **232** controls thresher settings of thresher **110**. In another example in which control system **214** receives a functional predictive map or a functional predictive map with control zones added, the settings controller **232** or another controller **246** controls material handling subsystem **125**. In another example in which control system **214** receives a functional predictive map or a functional predictive map with control zones added, the settings controller **232** controls crop cleaning subsystem **118**. In another example in which control system **214** receives a functional predictive map or a functional predictive map with control zones added, the machine cleaning controller **245** controls machine cleaning subsystem **254** on agricultural harvester **100**. In another example in which control system **214** receives a functional predictive map or a functional predictive map with control zones added, the communication system controller **229** controls communication system **206**. In another example in which control system **214** receives a functional predictive map or a functional predictive map with control zones added, the operator interface controller **231** controls operator interface mechanisms **218** on agricultural harvester **100**. In another example in which control system **214** receives the functional predictive map or the functional predictive map with control zones added, the deck plate position controller **242** controls machine/header actuators to control a deck plate on agricultural harvester **100**. In another example in which control system **214** receives the functional predictive map or the functional predictive map with control zones added, the draper belt controller **240** controls machine/header actuators to control a draper belt on agricultural harvester **100**. In another example in which control system **214** receives the functional predictive map or the functional predictive map with control zones added, the other controllers **246** control other controllable subsystems **256** on agricultural harvester **100**.

In one example, control system **214** may receive a functional predictive map or a functional predictive map with control zones added, and header/reel controller **238** can control header or other machine actuators **248**, to control a height, tilt, or roll of header **102** based upon the functional predictive map (with or without control zones). For instance, header/reel controller **238** can control header or other machine actuators **248** to adjust a height of header **102** above the surface of the field. In another example, header/reel controller **238** can control header or other machine actuators **248** to adjust a tilt of header, such as a tilt of header **102** from fore-to-aft (tilt can also referred to as a pitch). In another example, header/reel controller **238** can control header other machine actuators **238** to adjust a roll of header, such as a roll of header **102** from side-to-side, that is, across the width of header.

FIG. **8** shows a block diagram illustrating one example of control zone generator **213**. Control zone generator **213** includes work machine actuator (WMA) selector **486**, control zone generation system **488**, and regime zone generation system **490**. Control zone generator **213** may also include other items **492**. Control zone generation system **488** includes control zone criteria identifier component **494**, control zone boundary definition component **496**, target setting identifier component **498**, and other items **520**. Regime zone generation system **490** includes regime zone criteria identification component **522**, regime zone boundary definition component **524**, settings resolver identifier component **526**, and other items **528**. Before describing the overall operation of control zone generator **213** in more detail, a brief description of some of the items in control zone generator **213** and the respective operations thereof will first be provided.

Agricultural harvester **100**, or other work machines, may have a wide variety of different types of controllable actuators that perform different functions. The controllable actuators on agricultural harvester **100** or other work machines are collectively referred to as work machine actuators (WMAs). Each WMA may be independently controllable based upon values on a functional predictive map, or the WMAs may be controlled as sets based upon one or more values on a functional predictive map. Therefore, control zone generator **213** may generate control zones corresponding to each individually controllable WMA or corresponding to the sets of WMAs that are controlled in coordination with one another.

WMA selector **486** selects a WMA or a set of WMAs for which corresponding control zones are to be generated. Control zone generation system **488** then generates the control zones for the selected WMA or set of WMAs. For each WMA or set of WMAs, different criteria may be used in identifying control zones. For example, for one WMA, the WMA response time may be used as the criteria for defining the boundaries of the control zones. In another example, wear characteristics (e.g., how much a particular actuator or mechanism wears as a result of movement thereof) may be used as the criteria for identifying the boundaries of control zones. Control zone criteria identifier component **494** identifies particular criteria that are to be used in defining control zones for the selected WMA or set of WMAs. Control zone boundary definition component **496** processes the values on a functional predictive map under analysis to define the boundaries of the control zones on that functional predictive map based upon the values in the functional predictive map under analysis and based upon the control zone criteria for the selected WMA or set of WMAs.

Target setting identifier component **498** sets a value of the target setting that will be used to control the WMA or set of WMAs in different control zones. For instance, if the selected WMA is header or other machine actuators **248** and the functional predictive map under analysis is a functional predictive cut height characteristic map **1360**, then the target setting in each control zone may be a target header height, pitch, or roll setting based on cut height characteristic values contained in the functional predictive cut height characteristic map **1360**.

In some examples, where agricultural harvester **100** is to be controlled based on a current or future location of the agricultural harvester **100**, multiple target settings may be possible for a WMA at a given position. In that case, the target settings may have different values and may be competing. Thus, the target settings need to be resolved so that only a single target setting is used to control the WMA. For example, where the WMA is an actuator in propulsion system **250** that is being controlled in order to control the speed of agricultural harvester **100**, multiple different competing sets of criteria may exist that are considered by control zone generation system **488** in identifying the control zones and the target settings for the selected WMA in the control zones. For instance, different target settings for controlling header height, tilt, or roll may be generated based upon, for example, a detected or predicted cut height characteristic value (such as cut height or cut height variability), a detected or predicted agricultural characteristic value, a detected or predicted speed value, a detected or predicted topographic characteristic value (such as a slope value), a detected or predicted feed rate value, a detected or predictive fuel efficiency value, a detected or predicted grain loss value, or a combination of these. It will be noted that these are merely example, and target settings for various WMAs can be based on various other values or combinations of values. However, at any given time, the agricultural harvester **100** cannot travel over the ground with multiple header heights, multiple header tilts, or multiple header rolls simultaneously. Rather, at any given time, the agricultural harvester **100** has a single header height, a single header tilt, and a single header roll. Thus, one of the competing target settings is selected to control the height, tilt, or roll of the header of agricultural harvester **100**.

Therefore, in some examples, regime zone generation system **490** generates regime zones to resolve multiple different competing target settings. Regime zone criteria identification component **522** identifies the criteria that are used to establish regime zones for the selected WMA or set of WMAs on the functional predictive map under analysis. Some criteria that can be used to identify or define regime zones include, for example, cut height characteristics (such as cut height or cut height variability), agricultural characteristics, topographic characteristics (such as slope), speed characteristics (such as predictive speed values), operator command inputs, crop type or crop variety (for example based on an as-planted map or another source of the crop type or crop variety), weed type, weed intensity, or crop state (such as whether the crop is down, partially down or standing). These are merely some examples of the criteria that can be used to identify or define regime zones. Just as each WMA or set of WMAs may have a corresponding control zone, different WMAs or sets of WMAs may have a corresponding regime zone. Regime zone boundary definition component **524** identifies the boundaries of regime zones on the functional predictive map under analysis based on the regime zone criteria identified by regime zone criteria identification component **522**.

In some examples, regime zones may overlap with one another. For instance, a crop variety regime zone may overlap with a portion of or an entirety of a crop state regime zone. In such an example, the different regime zones may be assigned to a precedence hierarchy so that, where two or more regime zones overlap, the regime zone assigned with a greater hierarchical position or importance in the precedence hierarchy has precedence over the regime zones that have lesser hierarchical positions or importance in the precedence hierarchy. The precedence hierarchy of the regime zones may be manually set or may be automatically set using a rules-based system, a model-based system, or another system. As one example, where a downed crop regime zone overlaps with a crop variety regime zone, the downed crop regime zone may be assigned a greater importance in the precedence hierarchy than the crop variety regime zone so that the downed crop regime zone takes precedence.

In addition, each regime zone may have a unique settings resolver for a given WMA or set of WMAs. Settings resolver identifier component **526** identifies a particular settings resolver for each regime zone identified on the functional predictive map under analysis and a particular settings resolver for the selected WMA or set of WMAs.

Once the settings resolver for a particular regime zone is identified, that settings resolver may be used to resolve competing target settings, where more than one target setting is identified based upon the control zones. The different types of settings resolvers can have different forms. For instance, the settings resolvers that are identified for each regime zone may include a human choice resolver in which the competing target settings are presented to an operator or other user for resolution. In another example, the settings resolver may include a neural network or other artificial intelligence or machine learning system. In such instances, the settings resolvers may resolve the competing target settings based upon a predicted or historic quality metric corresponding to each of the different target settings. As an example, an increased vehicle speed setting may reduce the time to harvest a field and reduce corresponding time-based labor and equipment costs but may increase grain losses. A reduced vehicle speed setting may increase the time to harvest a field and increase corresponding time-based labor and equipment costs but may decrease grain losses. When grain loss or time to harvest is selected as a quality metric, the predicted or historic value for the selected quality metric, given the two competing vehicle speed settings values, may be used to resolve the speed setting. In some instances, the settings resolvers may be a set of threshold rules that may be used instead of, or in addition to, the regime zones. An example of a threshold rule may be expressed as follows:

If predicted biomass values within 20 feet of the header of the agricultural harvester **100** are greater that x kilograms (where x is a selected or predetermined value), then use the target setting value that is chosen based on feed rate over other competing target settings, otherwise use the target setting value based on grain loss over other competing target setting values.

The settings resolvers may be logical components that execute logical rules in identifying a target setting. For instance, the settings resolver may resolve target settings while attempting to minimize harvest time or minimize the total harvest cost or maximize harvested grain or based on other variables that are computed as a function of the different candidate target settings. A harvest time may be minimized when an amount to complete a harvest is reduced to at or below a selected threshold. A total harvest cost may be minimized where the total harvest cost is reduced to at or below a selected threshold. Harvested grain may be maximized where the amount of harvested grain is increased to at or above a selected threshold.

FIG. **9** is a flow diagram illustrating one example of the operation of control zone generator **213** in generating control zones and regime zones for a map that the control zone generator **213** receives for zone processing (e.g., for a map under analysis).

At block **530**, control zone generator **213** receives a map under analysis for processing. In one example, as shown at block **532**, the map under analysis is a functional predictive map. For example, the map under analysis may be one of the functional predictive maps **1360**, **427**, or **440**. Block **534** indicates that the map under analysis can be other maps as well.

At block **536**, WMA selector **486** selects a WMA or a set of WMAs for which control zones are to be generated on the map under analysis. At block **538**, control zone criteria identification component **494** obtains control zone definition criteria for the selected WMAs or set of WMAs. Block **540** indicates an example in which the control zone criteria are or include wear characteristics of the selected WMA or set of WMAs. Block **542** indicates an example in which the control zone definition criteria are or include a magnitude and variation of input source data, such as the magnitude and variation of the values on the map under analysis or the magnitude and variation of inputs from various in-situ sensors **208**. Block **544** indicates an example in which the control zone definition criteria are or include physical machine characteristics, such as the physical dimensions of the machine, a speed at which different subsystems operate, or other physical machine characteristics. Block **546** indicates an example in which the control zone definition criteria are or include a responsiveness of the selected WMA or set of WMAs in reaching newly commanded setting values. Block **548** indicates an example in which the control zone definition criteria are or include machine performance metrics. Block **550** indicates an example in which the control zone definition criteria are or includes operator preferences. Block **552** indicates an example in which the control zone definition criteria are or include other items as well. Block **549** indicates an example in which the control zone definition criteria are time based, meaning that agricultural harvester **100** will not cross the boundary of a control zone until a selected amount of time has elapsed since agricultural harvester **100** entered a particular control zone. In some instances, the selected amount of time may be a minimum amount of time. Thus, in some instances, the control zone definition criteria may prevent the agricultural harvester **100** from crossing a boundary of a control zone until at least the selected amount of time has elapsed. Block **551** indicates an example in which the control zone definition criteria are based on a selected size value. For example, control zone definition criteria that are based on a selected size value may preclude definition of a control zone that is smaller than the selected size. In some instances, the selected size may be a minimum size.

At block **554**, regime zone criteria identification component **522** obtains regime zone definition criteria for the selected WMA or set of WMAs. Block **556** indicates an example in which the regime zone definition criteria are based on a manual input from operator **260** or another user. Block **558** illustrates an example in which the regime zone definition criteria are based on topographic characteristics (such as slope). Block **559** illustrates an example in which the regime zone definition criteria are based on speed characteristics (such as speed values provided by functional predictive speed map **360**). Block **560** illustrates an example in which the regime zone definition criteria are based on cut height characteristics (such as cut height or cut height variability). Block **564** indicates an example in which the regime zone definition criteria are or include other criteria as well.

At block **566**, control zone boundary definition component **496** generates the boundaries of control zones on the map under analysis based upon the control zone criteria. Regime zone boundary definition component **524** generates the boundaries of regime zones on the map under analysis based upon the regime zone criteria. Block **568** indicates an example in which the zone boundaries are identified for the control zones and the regime zones. Block **570** shows that target setting identifier component **498** identifies the target settings for each of the control zones. The control zones and regime zones can be generated in other ways as well, and this is indicated by block **572**.

At block **574**, settings resolver identifier component **526** identifies the settings resolver for the selected WMAs in each regime zone defined by regimes zone boundary definition component **524**. As discussed above, the regime zone resolver can be a human resolver **576**, an artificial intelligence or machine learning system resolver **578**, a resolver **580** based on predicted or historic quality for each competing target setting, a rules-based resolver **582**, a performance criteria-based resolver **584**, or other resolvers **586**.

At block **588**, WMA selector **486** determines whether there are more WMAs or sets of WMAs to process. If additional WMAs or sets of WMAs are remaining to be processed, processing reverts to block **436** where the next WMA or set of WMAs for which control zones and regime zones are to be defined is selected. When no additional WMAs or sets of WMAs for which control zones or regime zones are to be generated are remaining, processing moves to block **590** where control zone generator **213** outputs a map with control zones, target settings, regime zones, and settings resolvers for each of the WMAs or sets of WMAs. As discussed above, the outputted map can be presented to operator **260** or another user; the outputted map can be provided to control system **214**; or the outputted map can be output in other ways.

FIG. **10** illustrates one example of the operation of control system **214** in controlling agricultural harvester **100** based upon a map that is output by control zone generator **213**. Thus, at block **592**, control system **214** receives a map of the worksite. In some instances, the map can be a functional predictive map that may include control zones and regime zones, as represented by block **594**. In some instances, the received map may be a functional predictive map that excludes control zones and regime zones. Block **596** indicates an example in which the received map of the worksite can be a prior information map having control zones and regime zones identified on it. Block **598** indicates an example in which the received map can include multiple different maps or multiple different map layers. Block **610** indicates an example in which the received map can take other forms as well.

At block **612**, control system **214** receives a sensor signal from geographic position sensor **204**. The sensor signal from geographic position sensor **204** can include data that indicates the geographic location **614** of agricultural harvester **100**, the speed **616** of agricultural harvester **100**, the heading **618** or agricultural harvester **100**, or other information **620**. At block **622**, zone controller **247** selects a regime zone, and, at block **624**, zone controller **247** selects a control zone on the map based on the geographic position sensor signal. At block **626**, zone controller **247** selects a WMA or a set of WMAs to be controlled. At block **628**, zone controller **247** obtains one or more target settings for the selected WMA or set of WMAs. The target settings that are obtained for the selected WMA or set of WMAs may come from a variety of different sources. For instance, block **630** shows an example in which one or more of the target settings for the selected WMA or set of WMAs is based on an input from the control zones on the map of the worksite. Block **632** shows an example in which one or more of the target settings is obtained from human inputs from operator **260** or another user. Block **634** shows an example in which the target settings are obtained from an in-situ sensor **208**. Block **636** shows an example in which the one or more target settings is obtained from one or more sensors on other machines working in the same field either concurrently with agricultural harvester **100** or from one or more sensors on machines that worked in the same field in the past. Block **638** shows an example in which the target settings are obtained from other sources as well.

At block **640**, zone controller **247** accesses the settings resolver for the selected regime zone and controls the settings resolver to resolve competing target settings into a resolved target setting. As discussed above, in some instances, the settings resolver may be a human resolver in which case zone controller **247** controls operator interface mechanisms **218** to present the competing target settings to operator **260** or another user for resolution. In some instances, the settings resolver may be a neural network or other artificial intelligence or machine learning system, and zone controller **247** submits the competing target settings to the neural network, artificial intelligence, or machine learning system for selection. In some instances, the settings resolver may be based on a predicted or historic quality metric, on threshold rules, or on logical components. In any of these latter examples, zone controller **247** executes the settings resolver to obtain a resolved target setting based on the predicted or historic quality metric, based on the threshold rules, or with the use of the logical components.

At block **642**, with zone controller **247** having identified the resolved target setting, zone controller **247** provides the resolved target setting to other controllers in control system **214**, which generate and apply control signals to the selected WMA or set of WMAs based upon the resolved target setting. For instance, where the selected WMA is a machine or header actuator **248**, zone controller **247** provides the resolved target setting to settings controller **232** or header/real controller **238** or both to generate control signals based upon the resolved target setting, and those generated control signals are applied to the machine or header actuators **248**. At block **644**, if additional WMAs or additional sets of WMAs are to be controlled at the current geographic location of the agricultural harvester **100** (as detected at block **612**), then processing reverts to block **626** where the next WMA or set of WMAs is selected. The processes represented by blocks **626** through **644** continue until all of the WMAs or sets of WMAs to be controlled at the current geographical location of the agricultural harvester **100** have been addressed. If no additional WMAs or sets of WMAs are to be controlled at the current geographic location of the agricultural harvester **100** remain, processing proceeds to block **646** where zone controller **247** determines whether additional control zones to be considered exist in the selected regime zone. If additional control zones to be considered exist, processing reverts to block **624** where a next control zone is selected. If no additional control zones are remaining to be considered, processing proceeds to block **648** where a determination as to whether additional regime zones are remaining to be consider. Zone controller **247** determines whether additional regime zones are remaining to be considered. If additional regimes zone are remaining to be considered, processing reverts to block **622** where a next regime zone is selected.

At block **650**, zone controller **247** determines whether the operation that agricultural harvester **100** is performing is complete. If not, the zone controller **247** determines whether a control zone criterion has been satisfied to continue processing, as indicated by block **652**. For instance, as mentioned above, control zone definition criteria may include criteria defining when a control zone boundary may be crossed by the agricultural harvester **100**. For example, whether a control zone boundary may be crossed by the agricultural harvester **100** may be defined by a selected time period, meaning that agricultural harvester **100** is prevented from crossing a zone boundary until a selected amount of time has transpired. In that case, at block **652**, zone controller **247** determines whether the selected time period has elapsed. Additionally, zone controller **247** can perform processing continually. Thus, zone controller **247** does not wait for any particular time period before continuing to determine whether an operation of the agricultural harvester **100** is completed. At block **652**, zone controller **247** determines that it is time to continue processing, then processing continues at block **612** where zone controller **247** again receives an input from geographic position sensor **204**. It will also be appreciated that zone controller **247** can control the WMAs and sets of WMAs simultaneously using a multiple-input, multiple-output controller instead of controlling the WMAs and sets of WMAs sequentially.

FIG. **11** is a block diagram showing one example of an operator interface controller **231**. In an illustrated example, operator interface controller **231** includes operator input command processing system **654**, other controller interaction system **656**, speech processing system **658**, and action signal generator **660**. Operator input command processing system **654** includes speech handling system **662**, touch gesture handling system **664**, and other items **666**. Other controller interaction system **656** includes controller input processing system **668** and controller output generator **670**. Speech processing system **658** includes trigger detector **672**, recognition component **674**, synthesis component **676**, natural language understanding system **678**, dialog management system **680**, and other items **682**. Action signal generator **660** includes visual control signal generator **684**, audio control signal generator **686**, haptic control signal generator **688**, and other items **690**. Before describing operation of the example operator interface controller **231** shown in FIG. **11** in handling various operator interface actions, a brief description of some of the items in operator interface controller **231** and the associated operation thereof is first provided.

Operator input command processing system **654** detects operator inputs on operator interface mechanisms **218** and processes those inputs for commands. Speech handling system **662** detects speech inputs and handles the interactions with speech processing system **658** to process the speech inputs for commands. Touch gesture handling system **664** detects touch gestures on touch sensitive elements in operator interface mechanisms **218** and processes those inputs for commands.

Other controller interaction system **656** handles interactions with other controllers in control system **214**. Controller input processing system **668** detects and processes inputs from other controllers in control system **214**, and controller output generator **670** generates outputs and provides those outputs to other controllers in control system **214**. Speech processing system **658** recognizes speech inputs, determines the meaning of those inputs, and provides an output indicative of the meaning of the spoken inputs. For instance, speech processing system **658** may recognize a speech input from operator **260** as a settings change command in which operator **260** is commanding control system **214** to change a setting for a controllable subsystem **216**. In such an example, speech processing system **658** recognizes the content of the spoken command, identifies the meaning of that command as a settings change command, and provides the meaning of that input back to speech handling system **662**. Speech handling system **662**, in turn, interacts with controller output generator **670** to provide the commanded output to the appropriate controller in control system **214** to accomplish the spoken settings change command.

Speech processing system **658** may be invoked in a variety of different ways. For instance, in one example, speech handling system **662** continuously provides an input from a microphone (being one of the operator interface mechanisms **218**) to speech processing system **658**. The microphone detects speech from operator **260**, and the speech handling system **662** provides the detected speech to speech processing system **658**. Trigger detector **672** detects a trigger indicating that speech processing system **658** is invoked. In some instances, when speech processing system **658** is receiving continuous speech inputs from speech handling system **662**, speech recognition component **674** performs continuous speech recognition on all speech spoken by operator **260**. In some instances, speech processing system **658** is configured for invocation using a wakeup word. That is, in some instances, operation of speech processing system **658** may be initiated based on recognition of a selected spoken word, referred to as the wakeup word. In such an example, where recognition component **674** recognizes the wakeup word, the recognition component **674** provides an indication that the wakeup word has been recognized to trigger detector **672**. Trigger detector **672** detects that speech processing system **658** has been invoked or triggered by the wakeup word. In another example, speech processing system **658** may be invoked by an operator **260** actuating an actuator on a user interface mechanism, such as by touching an actuator on a touch sensitive display screen, by pressing a button, or by providing another triggering input. In such an example, trigger detector **672** can detect that speech processing system **658** has been invoked when a triggering input via a user interface mechanism is detected. Trigger detector **672** can detect that speech processing system **658** has been invoked in other ways as well.

Once speech processing system **658** is invoked, the speech input from operator **260** is provided to speech recognition component **674**. Speech recognition component **674** recognizes linguistic elements in the speech input, such as words, phrases, or other linguistic units. Natural language understanding system **678** identifies a meaning of the recognized speech. The meaning may be a natural language output, a command output identifying a command reflected in the recognized speech, a value output identifying a value in the recognized speech, or any of a wide variety of other outputs that reflect the understanding of the recognized speech. For example, the natural language understanding system **678** and speech processing system **568**, more generally, may understand of the meaning of the recognized speech in the context of agricultural harvester **100**.

In some examples, speech processing system **658** can also generate outputs that navigate operator **260** through a user experience based on the speech input. For instance, dialog management system **680** may generate and manage a dialog with the user in order to identify what the user wishes to do. The dialog may disambiguate a user's command; identify one or more specific values that are needed to carry out the user's command; or obtain other information from the user or provide other information to the user or both. Synthesis component **676** may generate speech synthesis which can be presented to the user through an audio operator interface mechanism, such as a speaker. Thus, the dialog managed by dialog management system **680** may be exclusively a spoken dialog or a combination of both a visual dialog and a spoken dialog.

Action signal generator **660** generates action signals to control operator interface mechanisms **218** based upon outputs from one or more of operator input command processing system **654**, other controller interaction system **656**, and speech processing system **658**. Visual control signal generator **684** generates control signals to control visual items in operator interface mechanisms **218**. The visual items may be lights, a display screen, warning indicators, or other visual items. Audio control signal generator **686** generates outputs that control audio elements of operator interface mechanisms **218**. The audio elements include a speaker, audible alert mechanisms, horns, or other audible elements. Haptic control signal generator **688** generates control signals that are output to control haptic elements of operator interface mechanisms **218**. The haptic elements include vibration elements that may be used to vibrate, for example, the operator's seat, the steering wheel, pedals, or joysticks used by the operator. The haptic elements may include tactile feedback or force feedback elements that provide tactile feedback or force feedback to the operator through operator interface mechanisms. The haptic elements may include a wide variety of other haptic elements as well.

FIG. **12** is a flow diagram illustrating one example of the operation of operator interface controller **231** in generating an operator interface display on an operator interface mechanism **218**, which can include a touch sensitive display screen. FIG. **12** also illustrates one example of how operator interface controller **231** can detect and process operator interactions with the touch sensitive display screen.

At block **692**, operator interface controller **231** receives a map. Block **694** indicates an example in which the map is a functional predictive map, and block **696** indicates an example in which the map is another type of map. At block **698**, operator interface controller **231** receives an input from geographic position sensor **204** identifying the geographic location of the agricultural harvester **100**. As indicated in block **700**, the input from geographic position sensor **204** can include the heading, along with the location, of agricultural harvester **100**. Block **702** indicates an example in which the input from geographic position sensor **204** includes the speed of agricultural harvester **100**, and block **704** indicates an example in which the input from geographic position sensor **204** includes other items.

At block **706**, visual control signal generator **684** in operator interface controller **231** controls the touch sensitive display screen in operator interface mechanisms **218** to generate a display showing all or a portion of a field represented by the received map. Block **708** indicates that the displayed field can include a current position marker showing a current position of the agricultural harvester **100** relative to the field. Block **710** indicates an example in which the displayed field includes a next work unit marker that identifies a next work unit (or area on the field) in which agricultural harvester **100** will be operating. Block **712** indicates an example in which the displayed field includes an upcoming area display portion that displays areas that are yet to be processed by agricultural harvester **100**, and block **714** indicates an example in which the displayed field includes previously visited display portions that represent areas of the field that agricultural harvester **100** has already processed. Block **716** indicates an example in which the displayed field displays various characteristics of the field having georeferenced locations on the map. For instance, if the received map is a cut height characteristic map, such as predictive cut height characteristic map **1360**, the displayed field may show the different cut height characteristics existing in the field georeferenced within the displayed field. The mapped characteristics can be shown in the previously visited areas (as shown in block **714**), in the upcoming areas (as shown in block **712**), and in the next work unit (as shown in block **710**). Block **718** indicates an example in which the displayed field includes other items as well.

FIG. **13** is a pictorial illustration showing one example of a user interface display **720** that can be generated on a touch sensitive display screen. In other implementations, the user interface display **720** may be generated on other types of displays. The touch sensitive display screen may be mounted in the operator compartment of agricultural harvester **100** or on the mobile device or elsewhere. User interface display **720** will be described prior to continuing with the description of the flow diagram shown in FIG. **12**.

In the example shown in FIG. **13**, user interface display **720** illustrates that the touch sensitive display screen includes a display feature for operating a microphone **722** and a speaker **724**. Thus, the touch sensitive display may be communicably coupled to the microphone **722** and the speaker **724**. Block **726** indicates that the touch sensitive display screen can include a wide variety of user interface control actuators, such as buttons, keypads, soft keypads, links, icons, switches, etc. The operator **260** can actuator the user interface control actuators to perform various functions.

In the example shown in FIG. **13**, user interface display **720** includes a field display portion **728** that displays at least a portion of the field in which the agricultural harvester **100** is operating. The field display portion **728** is shown with a current position marker **708** that corresponds to a current position of agricultural harvester **100** in the portion of the field shown in field display portion **728**. In one example, the operator may control the touch sensitive display in order to zoom into portions of field display portion **728** or to pan or scroll the field display portion **728** to show different portions of the field. A next work unit **730** is shown as an area of the field directly in front of the current position marker **708** of agricultural harvester **100**. The current position marker **708** may also be configured to identify the direction of travel of agricultural harvester **100**, a speed of travel of agricultural harvester **100** or both. In FIG. **13**, the shape of the current position marker **708** provides an indication as to the orientation of the agricultural harvester **100** within the field which may be used as an indication of a direction of travel of the agricultural harvester **100**.

The size of the next work unit **730** marked on field display portion **728** may vary based upon a wide variety of different criteria. For instance, the size of next work unit **730** may vary based on the speed of travel of agricultural harvester **100**. Thus, when the agricultural harvester **100** is traveling faster, then the area of the next work unit **730** may be larger than the area of next work unit **730** if agricultural harvester **100** is traveling more slowly. In another example, the size of the next work unit **730** may vary based on the dimensions of the agricultural harvester **100**, including equipment on agricultural harvester **100** (such as header **102**). For example, the width of the next work unit **730** may vary based on a width of header **102**. Field display portion **728** is also shown displaying previously visited area **714** and upcoming areas **712**. Previously visited areas **714** represent areas that are already harvested while upcoming areas **712** represent areas that still need to be harvested. The field display portion **728** is also shown displaying different characteristics of the field. In the example illustrated in FIG. **13**, the map that is being displayed is a predictive cut height characteristic map, such as functional predictive cut height characteristic map **1360**. Therefore, a plurality of cut characteristic markers are displayed on field display portion **728**. There are a set of cut height characteristic display markers **732** shown in the already visited areas **714**. There are also a set of cut height characteristic display markers **732** shown in the upcoming areas **712**, and there are a set of cut height characteristic display markers **732** shown in the next work unit **730**. FIG. **13** shows that the cut characteristic display markers **732** are made up of different symbols that indicate an area of similar header characteristic values. In the example shown in FIG. **13**, the ! symbol represents areas of high cut height; the * symbol represents areas of ideal cut height; and the #symbol represents an area of low cut height.

Thus, the field display portion **728** shows different measured or predicted values (or characteristics indicated by the values) that are located at different areas within the field and represents those measured or predicted values (or characteristics indicated by or derived from the values) with a variety of display markers **732**. As shown, the field display portion **728** includes display markers, particularly cut height characteristic display markers **732** in the illustrated example of FIG. **13**, at particular locations associated with particular locations on the field being displayed. In some instances, each location of the field may have a display marker associated therewith. Thus, in some instances, a display marker may be provided at each location of the field display portion **728** to identify the nature of the characteristic being mapped for each particular location of the field. Consequently, the present disclosure encompasses providing a display marker, such as the cut height characteristic display marker **732** (as in the context of the present example of FIG. **13**), at one or more locations on the field display portion **728** to identify the nature, degree, etc., of the characteristic being displayed, thereby identifying the characteristic at the corresponding location in the field being displayed. As described earlier, the display markers **732** may be made up of different symbols, and, as described below, the symbols may be any display feature such as different colors, shapes, patterns, intensities, text, icons, or other display features.

In other examples, the map being displayed may be one or more of the maps described herein, including information maps, prior information maps, the functional predictive maps, such as predictive maps or predictive control zone maps, other predictive maps, or a combination thereof. Thus, the markers and characteristics being displayed will correlate to the information, data, characteristics, and values provided by the one or more maps being displayed.

In the example of FIG. **13**, user interface display **720** also has a control display portion **738**. Control display portion **738** allows the operator to view information and to interact with user interface display **720** in various ways.

The actuators and display markers in portion **738** may be displayed as, for example, individual items, fixed lists, scrollable lists, drop down menus, or drop down lists. In the example shown in FIG. **13**, display portion **738** shows information for the three different cut height categories that correspond to the three symbols mentioned above. Display portion **738** also includes a set of touch sensitive actuators with which the operator **260** can interact by touch. For example, the operator **260** may touch the touch sensitive actuators with a finger to activate the respective touch sensitive actuator. As shown, display portion **738** also includes a number of interactive tabs, such as cut height tab **762**, cut height variability tab **764**, and other tab **770**. Activating one of the tabs can modify which values are displayed in portions **728** and **738**. For instance, as shown, cut height tab **762** is activated, and, thus, the values mapped on portion **728** and shown in portion **738** correspond to cut height values of agricultural harvester **100**. When the operator **260** touches the tab **764**, touch gesture handling system **664** updates portion **728** and **738** to display characteristics relating to cut height variability values of agricultural harvester **100**. When the operator **260** touches the tab **770**, touch gesture handling system **664** updates portion **728** and **738** to display other cut height characteristics relating to agricultural harvester **100**, such as header height or header height variability.

As shown in FIG. **13**, display portion **738** includes an interactive flag display portion, indicated generally at **741**. Interactive flag display portion **741** includes a flag column **739** that shows flags that have been automatically or manually set. Flag actuator **740** allows operator **260** to mark a location, such as the current location of the agricultural harvester, or another location on the field designated by the operator and add information indicating the characteristic, such as cut height characteristics (e.g., cut height, cut height variability, etc.), found at the current location. For instance, when the operator **260** actuates the flag actuator **740** by touching the flag actuator **740**, touch gesture handling system **664** in operator interface controller **231** identifies the current location as one where agricultural harvester **100** had high cut height. When the operator **260** touches the button **742**, touch gesture handling system **664** identifies the current location as a location where agricultural harvester **100** had ideal cut height. When the operator **260** touches the button **744**, touch gesture handling system **664** identifies the current location as a location where agricultural harvester **100** had low cut height. Upon actuation of one of the flag actuators **740**, **742**, or **744**, touch gesture handling system **664** can control visual control signal generator **684** to add a symbol corresponding to the identified characteristic on field display portion **728** at a location the user identifies. In this way, areas of the field where the predicted value did not accurately represent an actual value can be marked for later analysis, and can also be used in machine learning. In other examples, the operator may designate areas ahead of or around the agricultural harvester **100** by actuating one of the flag actuators **740**, **742**, or **744** such that control of the agricultural harvester **100** can be undertaken based on the value designated by the operator **260**.

Display portion **738** also includes an interactive marker display portion, indicated generally at **743**. Interactive marker display portion **743** includes a symbol column **746** that displays the symbols corresponding to each category of values or characteristics (in the case of FIG. **13**, cut height characteristic) that is being tracked on the field display portion **728**. Display portion **738** also includes an interactive designator display portion, indicated generally at **745**. Interactive designator display portion **745** includes a designator column **748** that shows the designator (which may be a textual designator or other designator) identifying the category of values or characteristics (in the case of FIG. **13**, header characteristic). Without limitation, the symbols in symbol column **746** and the designators in designator column **748** can include any display feature such as different colors, shapes, patterns, intensities, text, icons, or other display features, and can be customizable by interaction of an operator of agricultural harvester **100**.

Display portion **738** also includes an interactive value display portion, indicated generally at **747**. Interactive value display portion **747** includes a value display column **750** that displays selected values. The selected values correspond to the characteristics or values being tracked or displayed, or both, on field display portion **728**. The selected values can be selected by an operator of the agricultural harvester **100**. The selected values in value display column **750** define a range of values or a value by which other values, such as predicted values, are to be classified. Thus, in the example in FIG. **13**, a predicted or measured cut height meeting or greater than 18 inches is classified as "high cut height", a predicted or measured cut height meeting 12 inches is classified as "ideal cut height", and a predicted or measured cut height meeting or less than 6 inches is classified as "low cut height." In some examples, the selected values may include a range, such that a predicted or measured value that is within the range of the selected value will be classified under the corresponding designator. For example, "ideal cut height", for instance, could include a range, such as 11-12 inches such that a measured or predicted cut height value falling within the range of 11-12 inches is classified as "ideal cut height". The selected values in value display column **750** are adjustable by an operator of agricultural harvester **100**. In one example, the operator **260** can select the particular part of field display portion **728** for which the values in column **750** are to be displayed. Thus, the values in column **750** can correspond to values in display portions **712**, **714** or **730**.

Display portion **738** also includes an interactive threshold display portion, indicated generally at **749**. Interactive threshold display portion **749** includes a threshold value display column **752** that displays action threshold values. Action threshold values in column **752** may be threshold values corresponding to the selected values in value display column **750**. If the predicted or measured values of characteristics being tracked or displayed, or both, satisfy the corresponding action threshold values in threshold value display column **752**, then control system **214** takes one or more actions identified in column **754**. In some instances, a measured or predicted value may satisfy a corresponding action threshold value by meeting or exceeding the corresponding action threshold value. In one example, operator **260** can select a threshold value, for example, in order to change the threshold value by touching the threshold value in threshold value display column **752**. Once selected, the operator **260** may change the threshold value. The threshold values in column **752** can be configured such that the designated action is performed when the measured or predicted value of the characteristic exceeds the threshold value, equals the threshold value, or is less than the threshold value. In some instances, the threshold value may represent a range of values, or range of deviation from the selected values in value display column **750**, such that a predicted or measured characteristic value that meets or falls within the range satisfies the threshold value. For instance, in the example of header characteristics, a predicted cut height value that falls within 2 inches of 18 inches will satisfy the corresponding action threshold value (of within 2 inches of 18 inches) and an action, such as adjusting the header position setting, adjusting the sensitivity setting, or adjusting the header ground pressure setting of the agricultural harvester will be taken by control system **214**. In other examples, the threshold values in column threshold value display column **752** are separate from the selected values in value display column **750**, such that the values in value display column **750** define the classification and display of predicted or measured values, while the action threshold values define when an action is to be taken based on the measured or predicted values. For example, while a predicted or measured cut height of 6 inches may be designated as "low cut height" for purposes of classification and display, the action threshold value may be 8 inches such that no action will be taken until the predicted or measured cut height satisfies the threshold value. In other examples, the threshold values in threshold value display column **752** may include distances or times. For instance, in the example of a distance, the threshold value may be a threshold distance from the area of the field where the measured or predicted value is georeferenced that the agricultural harvester **100** must be before an action is taken. For example, a threshold distance value of 5 feet would mean that an action will be taken when the agricultural harvester is at or within 5 feet of the area of the field where the measured or predicted value is georeferenced. In an example where the threshold value is time, the threshold value may be a threshold time for the agricultural harvester **100** to reach the area of the field where the measured or predictive value is georeferenced. For instance, a threshold value of 5 seconds would mean that an action will be taken when the agricultural harvester **100** is 5 seconds away from the area of the field where the measured or predicted value is georeferenced. In such an example, the current location and travel speed of the agricultural harvester can be accounted for.

Display portion **738** also includes an interactive action display portion, indicated generally at **751**. Interactive action display portion **751** includes an action display column **754** that displays action identifiers that indicate actions to be taken when a predicted or measured value satisfies an action threshold value in threshold value display column **752**. Operator **260** can touch the action identifiers in column **754** to change the action that is to be taken. When a threshold is satisfied, an action may be taken. For instance, at the bottom of column **754**, an adjust header position setting (such as a height setting, a pitch setting, or a roll setting), an adjust sensitivity setting, and an adjust ground pressure setting are identified as actions that will be taken if the measured or predicted value meets the threshold value in column **752**. In some examples, when a threshold is met, multiple actions may be taken. For instance, a header sensitivity setting may be adjusted (such as increased or decreased) and the ground pressure setting may be adjusted (such as increased or decreased). These are merely some examples.

The actions that can be set in column **754** can be any of a wide variety of different types of actions. For example, the actions can include a keep out action which, when executed, inhibits agricultural harvester **100** from further harvesting in an area. The actions can include a speed change action which, when executed, changes the travel speed of agricultural harvester **100** through the field. The actions can include a setting change action for changing a setting of an internal actuator or another WMA or set of WMAs or for implementing a settings change action that changes a setting, such as one or more header settings, such as a header position setting, a header sensitivity setting, and a header ground pressure setting. These are examples only, and a wide variety of other actions are contemplated herein.

The items shown on user interface display **720** can be visually controlled. Visually controlling the interface display **720** may be performed to capture the attention of operator **260**. For instance, the items can be controlled to modify the intensity, color, or pattern with which the items are displayed. Additionally, the items may be controlled to flash. The described alterations to the visual appearance of the items are provided as examples. Consequently, other aspects of the visual appearance of the items may be altered. Therefore, the items can be modified under various circumstances in a desired manner in order, for example, to capture the attention of operator **260**. Additionally, while a particular number of items are shown on user interface display **720**, this need not be the case. In other examples, more or less items, including more or less of a particular item can be included on user interface display **720**.

Returning now to the flow diagram of FIG. **12**, the description of the operation of operator interface controller **231** continues. At block **760**, operator interface controller **231** detects an input setting a flag and controls the touch sensitive user interface display **720** to display the flag on field display portion **728**. The detected input may be an operator input, as indicated at **762**, or an input from another controller, as indicated at **764**. At block **766**, operator interface controller **231** detects an in-situ sensor input indicative of a measured characteristic of the field from one of the in-situ sensors **208**. At block **768**, visual control signal generator **684** generates control signals to control user interface display **720** to display actuators for modifying user interface display **720** and for modifying machine control. For instance, block **770** represents that one or more of the actuators for setting or modifying the values in columns **739**, **746**, and **748** can be displayed. Thus, the user can set flags and modify characteristics of those flags. Block **772** represents that action threshold values in column **752** are displayed. Block **776** represents that the actions in column **754** are displayed, and block **778** represents that the selected values in column **750** are displayed. Block **780** indicates that a wide variety of other information and actuators can be displayed on user interface display **720** as well.

At block **782**, operator input command processing system **654** detects and processes operator inputs corresponding to interactions with the user interface display **720** performed by the operator **260**. Where the user interface mechanism on which user interface display **720** is displayed is a touch sensitive display screen, interaction inputs with the touch sensitive display screen by the operator **260** can be touch gestures **784**. In some instances, the operator interaction inputs can be inputs using a point and click device **786** or other operator interaction inputs **788**.

At block **790**, operator interface controller **231** receives signals indicative of an alert condition. For instance, block **792** indicates that signals may be received by controller input processing system **668** indicating that detected or predicted values satisfy threshold conditions present in column **752**. As explained earlier, the threshold conditions may include values being below a threshold, at a threshold, or above a threshold. Block **794** shows that action signal generator **660** can, in response to receiving an alert condition, alert the operator **260** by using visual control signal generator **684** to generate visual alerts, by using audio control signal generator **686** to generate audio alerts, by using haptic control signal generator **688** to generate haptic alerts, or by using any combination of these. Similarly, as indicated by block **796**, controller output generator **670** can generate outputs to other controllers in control system **214** so that those controllers perform the corresponding action identified in column **754**. Block **798** shows that operator interface controller **231** can detect and process alert conditions in other ways as well.

Block **900** shows that speech handling system **662** may detect and process inputs invoking speech processing system **658**. Block **902** shows that performing speech processing may include the use of dialog management system **680** to conduct a dialog with the operator **260**. Block **904** shows that the speech processing may include providing signals to controller output generator **670** so that control operations are automatically performed based upon the speech inputs.

Table 1, below, shows an example of a dialog between operator interface controller **231** and operator **260**. In Table 1, operator **260** uses a trigger word or a wakeup word that is detected by trigger detector **672** to invoke speech processing system **658**. In the example shown in Table 1, the wakeup word is "Johnny".

TABLE 1

Operator: "Johnny, tell me about current cut height characteristics"
Operator Interface Controller: "Cut height is currently high."
Operator: "Johnny, what should I do because of the cut height?"
Operator Interface Controller: "Adjust header sensitivity setting."

Table 2 shows an example in which speech synthesis component **676** provides an output to audio control signal generator **686** to provide audible updates on an intermittent or periodic basis. The interval between updates may be time-based, such as every five minutes, or coverage or distance-based, such as every five acres, or exception-based, such as when a measured value is greater than a threshold value.

TABLE 2

Operator Interface Controller: "Over last 10 seconds, cut height has varied beyond ideal cut height."
Operator Interface Controller: "Next 1 acre predicted cut height is low."
Operator Interface Controller: "Caution: upcoming change in slope, header height increased."

The example shown in Table 3 illustrates that some actuators or user input mechanisms on the touch sensitive display **720** can be supplemented with speech dialog. The example in Table 3 illustrates that action signal generator **660** can generate action signals to automatically mark a cut height characteristic area in the field being harvested.

TABLE 3

Human: "Johnny, mark high cut height variability area."
Operator Interface Controller: "High cut height variability area marked."

The example shown in Table 4 illustrates that action signal generator **660** can conduct a dialog with operator **260** to begin and end marking of a cut height characteristic area.

TABLE 4

Human: "Johnny, start marking high cut height area."
Operator Interface Controller: "Marking high cut height area."
Human: "Johnny, stop marking high cut height area."
Operator Interface Controller: "High cut height area marking stopped."

The example shown in Table 5 illustrates that action signal generator **160** can generate signals to mark a cut height characteristic area in a different way than those shown in Tables 3 and 4.

TABLE 5

Human: "Johnny, mark the last 100 feet as a low cut height area."
Operator Interface Controller: "Last 100 feet marked as a low cut height area."

Returning again to FIG. **12**, block **906** illustrates that operator interface controller **231** can detect and process conditions for outputting a message or other information in other ways as well. For instance, other controller interaction system **656** can detect inputs from other controllers indicating that alerts or output messages should be presented to operator **260**. Block **908** shows that the outputs can be audio messages. Block **910** shows that the outputs can be visual messages, and block **912** shows that the outputs can be haptic messages. Until operator interface controller **231** determines that the current harvesting operation is completed, as indicated by block **914**, processing reverts to block **698** where the geographic location of harvester **100** is updated and processing proceeds as described above to update user interface display **720**.

Once the operation is complete, then any desired values that are displayed, or have been displayed on user interface display **720**, can be saved. Those values can also be used in machine learning to improve different portions of predictive model generator **210**, predictive map generator **212**, control zone generator **213**, control algorithms, or other items. Saving the desired values is indicated by block **916**. The values can be saved locally on agricultural harvester **100**, or the values can be saved at a remote server location or sent to another remote system.

It can thus be seen that one or more maps are obtained by an agricultural harvester that show agricultural characteristic values at different geographic locations of a field being harvested. An in-situ sensor on the harvester senses a characteristic that has values indicative of a cut height characteristic as the agricultural harvester moves through the field. A predictive map generator generates a predictive map that predicts control values for different locations in the field based on the values of the agricultural characteristic in the map and the agricultural characteristic sensed by the in-situ sensor. A control system controls controllable subsystem based on the control values in the predictive map.

A control value is a value upon which an action can be based. A control value, as described herein, can include any value (or characteristics indicated by or derived from the value) that may be used in the control of agricultural harvester **100**. A control value can be any value indicative of an agricultural characteristic. A control value can be a predicted value, a measured value, or a detected value. A control value may include any of the values provided by a map, such as any of the maps described herein, for instance, a control value can be a value provided by an information map, a value provided by prior information map, or a value provided predictive map, such as a functional predictive map. A control value can also include any of the characteristics indicated by or derived from the values detected by any of the sensors described herein. In other examples, a control value can be provided by an operator of the agricultural machine, such as a command input by an operator of the agricultural machine.

The present discussion has mentioned processors and servers. In some examples, the processors and servers include computer processors with associated memory and timing circuitry, not separately shown. The processors and servers are functional parts of the systems or devices to which the processors and servers belong and are activated by and facilitate the functionality of the other components or items in those systems.

Also, a number of user interface displays have been discussed. The displays can take a wide variety of different forms and can have a wide variety of different user actuatable operator interface mechanisms disposed thereon. For instance, user actuatable operator interface mechanisms may include text boxes, check boxes, icons, links, drop-down menus, search boxes, etc. The user actuatable operator interface mechanisms can also be actuated in a wide variety of different ways. For instance, the user actuatable operator interface mechanisms can be actuated using operator interface mechanisms such as a point and click device, such as a track ball or mouse, hardware buttons, switches, a joystick or keyboard, thumb switches or thumb pads, etc., a virtual keyboard or other virtual actuators. In addition, where the screen on which the user actuatable operator interface mechanisms are displayed is a touch sensitive screen, the user actuatable operator interface mechanisms can be actuated using touch gestures. Also, user actuatable operator interface mechanisms can be actuated using speech commands using speech recognition functionality. Speech recognition may be implemented using a speech detection device, such as a microphone, and software that functions to recognize detected speech and execute commands based on the received speech.

A number of data stores have also been discussed. It will be noted the data stores can each be broken into multiple data stores. In some examples, one or more of the data stores may be local to the systems accessing the data stores, one or more of the data stores may all be located remote form a system utilizing the data store, or one or more data stores may be local while others are remote. All of these configurations are contemplated by the present disclosure.

Also, the figures show a number of blocks with functionality ascribed to each block. It will be noted that fewer blocks can be used to illustrate that the functionality ascribed to multiple different blocks is performed by fewer components. Also, more blocks can be used illustrating that the functionality may be distributed among more components. In different examples, some functionality may be added, and some may be removed.

It will be noted that the above discussion has described a variety of different systems, components, logic, and interactions. It will be appreciated that any or all of such systems, components, logic and interactions may be implemented by hardware items, such as processors, memory, or other processing components, including but not limited to artificial intelligence components, such as neural networks, some of which are described below, that perform the functions associated with those systems, components, logic, or interactions. In addition, any or all of the systems, components, logic and interactions may be implemented by software that is loaded into a memory and is subsequently executed by a processor or server or other computing component, as described below. Any or all of the systems, components, logic and interactions may also be implemented by different combinations of hardware, software, firmware, etc., some examples of which are described below. These are some examples of different structures that may be used to implement any or all of the systems, components, logic and interactions described above. Other structures may be used as well.

FIG. **14** is a block diagram of agricultural harvester **600**, which may be similar to agricultural harvester **100** shown in FIG. **2**. The agricultural harvester **600** communicates with elements in a remote server architecture **500**. In some examples, remote server architecture **500** provides computation, software, data access, and storage services that do not require end-user knowledge of the physical location or configuration of the system that delivers the services. In various examples, remote servers may deliver the services over a wide area network, such as the internet, using appropriate protocols. For instance, remote servers may deliver applications over a wide area network and may be accessible through a web browser or any other computing component. Software or components shown in FIG. **2** as well as data associated therewith, may be stored on servers at a remote location. The computing resources in a remote server environment may be consolidated at a remote data center location, or the computing resources may be dispersed to a plurality of remote data centers. Remote server infrastructures may deliver services through shared data centers, even though the services appear as a single point of access for the user. Thus, the components and functions described herein may be provided from a remote server at a remote location using a remote server architecture. Alternatively, the components and functions may be provided from a server, or the components and functions can be installed on client devices directly, or in other ways.

In the example shown in FIG. **14**, some items are similar to those shown in FIG. **2** and those items are similarly numbered. FIG. **14** specifically shows that predictive model generator **210** or predictive map generator **212**, or both, may be located at a server location **502** that is remote from the agricultural harvester **600**. Therefore, in the example shown in FIG. **14**, agricultural harvester **600** accesses systems through remote server location **502**.

FIG. **14** also depicts another example of a remote server architecture. FIG. **14** shows that some elements of FIG. **2** may be disposed at a remote server location **502** while others may be located elsewhere. By way of example, data store **202** may be disposed at a location separate from location **502** and accessed via the remote server at location **502**. Regardless of where the elements are located, the elements can be accessed directly by agricultural harvester **600** through a network such as a wide area network or a local area network; the elements can be hosted at a remote site by a service; or the elements can be provided as a service or accessed by a connection service that resides in a remote location. Also, data may be stored in any location, and the stored data may be accessed by, or forwarded to, operators, users, or systems. For instance, physical carriers may be used instead of, or in addition to, electromagnetic wave carriers. In some examples, where wireless telecommunication service coverage is poor or nonexistent, another machine, such as a fuel truck or other mobile machine or vehicle, may have an automated, semi-automated, or manual information collection system. As the combine harvester **600** comes close to the machine containing the information collection system, such as a fuel truck prior to fueling, the information collection system collects the information from the combine harvester **600** using any type of ad-hoc wireless connection. The collected information may then be forwarded to another network when the machine containing the received information reaches a location where wireless telecommunication service coverage or other wireless coverage—is available. For instance, a fuel truck may enter an area having wireless communication coverage when traveling to a location to fuel other machines or when at a main fuel storage location. All of these architectures are contemplated herein. Further, the information may be stored on the agricultural harvester **600** until the agricultural harvester **600** enters an area having wireless communication coverage. The agricultural harvester **600**, itself, may send the information to another network.

It will also be noted that the elements of FIG. **2**, or portions thereof, may be disposed on a wide variety of different devices. One or more of those devices may include an on-board computer, an electronic control unit, a display unit, a server, a desktop computer, a laptop computer, a tablet computer, or other mobile device, such as a palm top computer, a cell phone, a smart phone, a multimedia player, a personal digital assistant, etc.

In some examples, remote server architecture **500** may include cybersecurity measures. Without limitation, these measures may include encryption of data on storage devices, encryption of data sent between network nodes, authentication of people or processes accessing data, as well as the use of ledgers for recording metadata, data, data transfers, data accesses, and data transformations. In some examples, the ledgers may be distributed and immutable (e.g., implemented as blockchain).

FIG. **15** is a simplified block diagram of one illustrative example of a handheld or mobile computing device that can be used as a user's or client's hand held device **16**, in which the present system (or parts of it) can be deployed. For instance, a mobile device can be deployed in the operator compartment of agricultural harvester **100** for use in generating, processing, or displaying the maps discussed above. FIGS. **16-17** are examples of handheld or mobile devices.

FIG. **15** provides a general block diagram of the components of a client device **16** that can run some components shown in FIG. **2**, that interacts with them, or both. In the device **16**, a communications link **13** is provided that allows the handheld device to communicate with other computing devices and under some examples provides a channel for receiving information automatically, such as by scanning. Examples of communications link **13** include allowing communication though one or more communication protocols, such as wireless services used to provide cellular access to a network, as well as protocols that provide local wireless connections to networks.

In other examples, applications can be received on a removable Secure Digital (SD) card that is connected to an interface **15**. Interface **15** and communication links **13** communicate with a processor **17** (which can also embody processors or servers from other FIGS.) along a bus **19** that is also connected to memory **21** and input/output (I/O) components **23**, as well as clock **25** and location system **27**.

I/O components **23**, in one example, are provided to facilitate input and output operations. I/O components **23** for various examples of the device **16** can include input components such as buttons, touch sensors, optical sensors, microphones, touch screens, proximity sensors, accelerometers, orientation sensors and output components such as a display device, a speaker, and or a printer port. Other I/O components **23** can be used as well.

Clock **25** illustratively comprises a real time clock component that outputs a time and date. It can also, illustratively, provide timing functions for processor **17**.

Location system **27** illustratively includes a component that outputs a current geographical location of device **16**. This can include, for instance, a global positioning system (GPS) receiver, a LORAN system, a dead reckoning system, a cellular triangulation system, or other positioning system. Location system **27** can also include, for example, mapping software or navigation software that generates desired maps, navigation routes and other geographic functions.

Memory **21** stores operating system **29**, network settings **31**, applications **33**, application configuration settings **35**, data store **37**, communication drivers **39**, and communication configuration settings **41**. Memory **21** can include all types of tangible volatile and non-volatile computer-readable memory devices. Memory **21** may also include computer storage media (described below). Memory **21** stores computer readable instructions that, when executed by processor **17**, cause the processor to perform computer-implemented steps or functions according to the instructions. Processor **17** may be activated by other components to facilitate their functionality as well.

FIG. **16** shows one example in which device **16** is a tablet computer **600**. In FIG. **16**, computer **601** is shown with user interface display screen **602**. Screen **602** can be a touch screen or a pen-enabled interface that receives inputs from a pen or stylus. Tablet computer **600** may also use an on-screen virtual keyboard. Of course, computer **601** might also be attached to a keyboard or other user input device through a suitable attachment mechanism, such as a wireless link or USB port, for instance. Computer **601** may also illustratively receive voice inputs as well.

FIG. **17** is similar to FIG. **16** except that the device is a smart phone **71**. Smart phone **71** has a touch sensitive display **73** that displays icons or tiles or other user input mechanisms **75**. Mechanisms **75** can be used by a user to run applications, make calls, perform data transfer operations, etc. In general, smart phone **71** is built on a mobile operating system and offers more advanced computing capability and connectivity than a feature phone.

Note that other forms of the devices **16** are possible.

FIG. **18** is one example of a computing environment in which elements of FIG. **2** can be deployed. With reference to FIG. **18**, an example system for implementing some embodiments includes a computing device in the form of a computer **810** programmed to operate as discussed above. Components of computer **810** may include, but are not limited to, a processing unit **820** (which can comprise processors or servers from previous FIGS.), a system memory **830**, and a system bus **821** that couples various system components including the system memory to the processing unit **820**. The system bus **821** may be any of several types of bus structures including a memory bus or memory controller, a peripheral bus, and a local bus using any of a variety of bus architectures. Memory and programs described with respect to FIG. **2** can be deployed in corresponding portions of FIG. **18**.

Computer **810** typically includes a variety of computer readable media. Computer readable media may be any available media that can be accessed by computer **810** and includes both volatile and nonvolatile media, removable and non-removable media. By way of example, and not limitation, computer readable media may comprise computer storage media and communication media. Computer storage media is different from, and does not include, a modulated data signal or carrier wave. Computer readable media includes hardware storage media including both volatile and nonvolatile, removable and non-removable media implemented in any method or technology for storage of information such as computer readable instructions, data structures, program modules or other data. Computer storage media includes, but is not limited to, RAM, ROM, EEPROM, flash memory or other memory technology, CD-ROM, digital versatile disks (DVD) or other optical disk storage, magnetic cassettes, magnetic tape, magnetic disk storage or other magnetic storage devices, or any other medium which can be used to store the desired information and which can be accessed by computer **810**. Communication media may embody computer readable instructions, data structures, program modules or other data in a transport mechanism and includes any information delivery media. The term "modulated data signal" means a signal that has one or more of its characteristics set or changed in such a manner as to encode information in the signal.

The system memory **830** includes computer storage media in the form of volatile and/or nonvolatile memory or both such as read only memory (ROM) **831** and random access memory (RAM) **832**. A basic input/output system **833** (BIOS), containing the basic routines that help to transfer information between elements within computer **810**, such as during start-up, is typically stored in ROM **831**. RAM **832** typically contains data or program modules or both that are immediately accessible to and/or presently being operated on by processing unit **820**. By way of example, and not limitation, FIG. **18** illustrates operating system **834**, application programs **835**, other program modules **836**, and program data **837**.

The computer **810** may also include other removable/non-removable volatile/nonvolatile computer storage media. By way of example only, FIG. **18** illustrates a hard disk drive **841** that reads from or writes to non-removable, nonvolatile magnetic media, an optical disk drive **855**, and nonvolatile optical disk **856**. The hard disk drive **841** is typically connected to the system bus **821** through a non-removable memory interface such as interface **840**, and optical disk drive **855** are typically connected to the system bus **821** by a removable memory interface, such as interface **850**.

Alternatively, or in addition, the functionality described herein can be performed, at least in part, by one or more hardware logic components. For example, and without limitation, illustrative types of hardware logic components that can be used include Field-programmable Gate Arrays (FPGAs), Application-specific Integrated Circuits (e.g., ASICs), Application-specific Standard Products (e.g., ASSPs), System-on-a-chip systems (SOCs), Complex Programmable Logic Devices (CPLDs), etc.

The drives and their associated computer storage media discussed above and illustrated in FIG. **18**, provide storage of computer readable instructions, data structures, program modules and other data for the computer **810**. In FIG. **18**, for example, hard disk drive **841** is illustrated as storing operating system **844**, application programs **845**, other program modules **846**, and program data **847**. Note that these components can either be the same as or different from operating system **834**, application programs **835**, other program modules **836**, and program data **837**.

A user may enter commands and information into the computer **810** through input devices such as a keyboard **862**, a microphone **863**, and a pointing device **861**, such as a mouse, trackball or touch pad. Other input devices (not shown) may include a joystick, game pad, satellite dish, scanner, or the like. These and other input devices are often connected to the processing unit **820** through a user input interface **860** that is coupled to the system bus, but may be connected by other interface and bus structures. A visual display **891** or other type of display device is also connected to the system bus **821** via an interface, such as a video interface **890**. In addition to the monitor, computers may also include other peripheral output devices such as speakers **897** and printer **896**, which may be connected through an output peripheral interface **895**.

The computer **810** is operated in a networked environment using logical connections (such as a controller area network—CAN, local area network—LAN, or wide area network WAN) to one or more remote computers, such as a remote computer **880**.

When used in a LAN networking environment, the computer **810** is connected to the LAN **871** through a network interface or adapter **870**. When used in a WAN networking environment, the computer **810** typically includes a modem **872** or other means for establishing communications over the WAN **873**, such as the Internet. In a networked environment, program modules may be stored in a remote memory storage device. FIG. **18** illustrates, for example, that remote application programs **885** can reside on remote computer **880**.

It should also be noted that the different examples described herein can be combined in different ways. That is, parts of one or more examples can be combined with parts of one or more other examples. All of this is contemplated herein.

Example 1 is an agricultural work machine comprising:

a communication system that receives a map that includes values of a cut height characteristic corresponding to different locations in a field;

a geographic position sensor that detects a geographic location of the agricultural work machine;

an in-situ sensor that detects a value of an agricultural characteristic corresponding to the geographic location;

a predictive map generator that generates a functional predictive agricultural map of the field that maps predictive control values to the different geographic locations in the field based on the values of the cut height characteristic in the map and based on the value of the agricultural characteristic;

a controllable subsystem; and

a control system that generates a control signal to control the controllable subsystem based on the geographic location of the agricultural work machine and based on the control values in the functional predictive agricultural map.

Example 2 is the agricultural work machine of any or all previous examples, wherein the map comprises a predictive cut height characteristic map that includes, as values of the cut height characteristic, predictive values of the cut height characteristic corresponding to the different locations in the field.

Example 3 is the agricultural work machine of any or all previous examples, wherein the predictive map generator comprises:

a predictive agricultural characteristic map generator that generates, as the functional predictive agricultural map, a functional predictive agricultural characteristic map that maps, as the predictive control values, predictive values of the agricultural characteristic to the different geographic locations in the field.

Example 4 is the agricultural work machine of any or all previous examples, wherein the in-situ sensor detects, as the value of the agricultural characteristic, a value of an operator command indicative of a commanded action of the agricultural work machine.

Example 5 is the agricultural work machine of any or all previous examples, wherein the predictive map generator comprises:

a predictive operator command map that generates, as the functional predictive agricultural map, a functional predictive operator command map that maps, as the predictive control values, predictive operator command values to the different geographic locations in the field.

Example 6 is the agricultural work machine of any or all previous examples, wherein the control system comprises:

a settings controller that generates an operator command control signal indicative of an operator command based on the detected geographic location and the functional predictive operator command map and controls the controllable subsystem based on the operator command control signal to execute the operator command.

Example 7 is the agricultural work machine of any or all previous examples, wherein the control system generates the control signal to control the controllable subsystem to adjust a setting of a header on the agricultural work machine.

Example 8 is the agricultural work machine of any or all previous examples and further comprising:

a predictive model generator that generates a predictive agricultural model that models a relationship between the cut height characteristic and the agricultural characteristic based on a value of the cut height characteristic in the map at the geographic location and the value of the agricultural characteristic detected by the in-situ sensor corresponding to the geographic location, wherein the predictive map generator generates the functional predictive agricultural map based on the values of the cut height characteristic in the map and based on the predictive agricultural model.

Example 9 is the agricultural work machine of any or all previous examples, wherein the control system further comprises:

an operator interface controller that generates a user interface map representation of the functional predictive agricultural map, the user interface map representation comprising a field portion with one or more markers indicating the predictive control values at one or more geographic locations on the field portion.

Example 10 is the agricultural work machine of any or all previous examples, wherein the operator interface controller generates the user interface map representation to include an interactive display portion that displays a value display portion indicative of a selected value, an interactive threshold display portion indicative of an action threshold, and an interactive action display portion indicative of a control action to be taken when one of the predictive control values satisfies the action threshold in relation to the selected value, the control system generating the control signal to control the controllable subsystem based on the control action.

Example 11 is a computer implemented method of controlling an agricultural work machine comprising:

obtaining a map that includes values of a cut height characteristic corresponding to different geographic locations in a field;

detecting a geographic location of the agricultural work machine;

detecting, with an in-situ sensor, a value of an agricultural characteristic corresponding to the geographic location;

generating a functional predictive agricultural map of the field that maps predictive control values to the different geographic locations in the field based on the values of the cut height characteristic in the map and based on the value of the agricultural characteristic; and

controlling a controllable subsystem based on the geographic location of the agricultural work machine and based on the control values in the functional predictive agricultural map.

Example 12 is the computer implemented method of any or all previous examples, wherein obtaining the map comprises:

obtaining a predictive cut height characteristic map that includes, as values of the cut height characteristic, predictive values of the cut height characteristic corresponding to the different geographic locations in the field.

Example 13 is the computer implemented method of any or all previous examples, wherein generating the functional predictive agricultural map comprises:

generating a functional predictive agricultural characteristic map that maps, as the predictive control values, predictive values of the agricultural characteristic to the different geographic locations in the field.

Example 14 is the computer implemented method of any or all previous examples, wherein detecting, with an in-situ sensor, the value of an agricultural characteristic comprises:

detecting, with the in-situ sensor, as the value of the agricultural characteristic, an operator command indicative of a commanded action of the agricultural work machine.

Example 15 is the computer implemented method of any or all previous examples, wherein generating the functional predictive agricultural map comprises:

generating a functional predictive operator command map that maps, as the predictive control values, predictive operator command values to the different geographic locations in the field.

Example 16 is the computer implemented method of any or all previous examples, wherein controlling the controllable subsystem comprises:

generating an operator command control signal indicative of an operator command based on the detected geographic location and the functional predictive operator command map; and

controlling the controllable subsystem based on the operator command control signal to execute the operator command.

Example 17 is the computer implemented method of any or all previous examples, wherein controlling the controllable subsystem comprises:

controlling the controllable subsystem to adjust a setting of a header on the agricultural work machine.

Example 18 is the computer implemented method of any or all previous examples and further comprising:

generating a predictive agricultural model that models a relationship between the cut height characteristic and the agricultural characteristic based on a value of the cut height characteristic in the map at the geographic location and the value of the agricultural characteristic detected by the in-situ sensor corresponding to the geographic location, wherein generating the functional predictive agricultural map comprises generating the functional predictive agricultural map based on the values of the cut height characteristic in the map and based on the predictive agricultural model.

Example 19 is an agricultural work machine comprising:

a communication system that receives a map that includes values of a cut height characteristic corresponding to different geographic locations in a field;

a geographic position sensor that detects a geographic location of the agricultural work machine

an in-situ sensor that detects a value of an agricultural characteristic corresponding to the geographic location;

a predictive model generator that generates a predictive agricultural model that models a relationship between the cut height characteristic and the agricultural characteristic based on a value of the cut height characteristic in the map at the geographic location and the value of the agricultural characteristic detected by the in-situ sensor corresponding to the geographic location;

a predictive map generator that generates a functional predictive agricultural map of the field that maps predictive control values to the different geographic locations in the field based on the values of the cut height characteristic in the map and based on the predictive agricultural model;

a controllable subsystem; and

a control system that generates a control signal to control the controllable subsystem based on the geographic position of the agricultural work machine and based on the control values in the functional predictive agricultural map.

Example 20 is the agricultural work machine of any or all previous examples wherein the control signal control the controllable subsystem to adjust a setting of a header on the agricultural work machine based on the detected geographic location and the functional predictive agricultural map.

Although the subject matter has been described in language specific to structural features or methodological acts, it is to be understood that the subject matter defined in the appended claims is not necessarily limited to the specific features or acts described above. Rather, the specific features and acts described above are disclosed as example forms of the claims.

What is claimed is:

1. An agricultural work machine comprising:

a communication system that receives an information map that includes values of a first agricultural characteristic corresponding to a set of locations in a field, wherein the first agricultural characteristic comprises cut height or cut height variability;

an in-situ sensor that detects a value of a second agricultural characteristic, different than the first agricultural characteristic, corresponding to a first location of the set of locations in the field;

a predictive model generator that generates a predictive model that models a relationship between values of the first characteristic and values of the second characteristic based, at least, on a value of the first agricultural characteristic, in the information map, corresponding to the first location and the detected value of the second agricultural characteristic corresponding to the first location;

a predictive map generator that maps a predictive value of the second agricultural characteristic at a second location of the set of locations in the field based on a value of the first agricultural characteristic, in the map, corresponding to the second location and the model;

a controllable subsystem; and

a control system that generates, as the agricultural work machine performs the operation at the field, a control signal to control the controllable subsystem based on the mapped predictive value of the second agricultural characteristic corresponding to the second location.

2. The agricultural work machine of claim **1**, wherein the in-situ sensor detects, as the value of the second agricultural characteristic, a value of an operator command indicative of a commanded action of the agricultural work machine at the first location.

3. The agricultural work machine of claim **2**, wherein the predictive map generator comprises;

a predictive operator command map generator that generates, as a functional predictive agricultural map, a functional predictive operator command map that maps, as the predictive value of the second agricultural characteristic, a predictive operator command value to the second location in the field.

4. The agricultural work machine of claim **3**, wherein the control system comprises:

a settings controller that generates, as the control signal, an operator command control signal indicative of an operator command based on the functional predictive operator command map and controls the controllable subsystem based on the operator command control signal to execute the operator command.

5. The agricultural work machine of claim **1**, wherein the control system generates the control signal to control the controllable subsystem to adjust a setting of a header on the agricultural work machine.

6. The agricultural work machine of claim **1**, wherein the predictive model is configured to receive the value of the first agricultural characteristic in the map corresponding the second geographic location as a model input and provide the predictive value of the agricultural characteristic at the second geographic location as a model output.

7. The agricultural work machine of claim **1**, wherein the control system further comprises:

an operator interface controller that generates a user interface map representation based on the mapped predictive value, the user interface map representation comprising a field portion with a marker indicating the mapped predictive value of the second agricultural characteristic at the second location on the field portion.

8. The agricultural work machine of claim **7**, wherein the operator interface controller generates the user interface map representation to include an interactive display portion that displays a value display portion indicative of a selected value, an interactive threshold display portion indicative of an action threshold, and an interactive action display portion indicative of a control action to be taken when the predictive value of the second agricultural characteristic satisfies the action threshold in relation to the selected value, the control system generating the control signal to control the controllable subsystem based on the control action.

9. The agricultural work machine of claim **1**, wherein the communication system receives the information map that includes values of a third agricultural characteristic corresponding to the set of locations in the field, the work machine further comprising;

an in-situ cut height characteristic sensor that detects a value of the cut height characteristic corresponding to a third geographic location;

a predictive cut height characteristic map generator predictive values of the cut height characteristic corresponding to the set of locations in the field based on the detected value of the cut height characteristic corresponding to the third geographic location and based on a value of the third agricultural characteristic in the information map at the third geographic location.

10. The agricultural work machine of claim **9**, wherein the information map comprises:

a speed map that maps, as the values of the third agricultural characteristic, values of a speed characteristic of the agricultural work machine to the set of locations in the field.

11. The agricultural work machine of claim **1**, wherein the controllable subsystem comprises a first controllable subsystem and wherein the computer executable instructions, when executed by the one or more processors, further configure the one or more processors to:

generate, during a current operation at the field, a functional predictive control zone map of the field that maps a first plurality of control zones corresponding to the first controllable subsystem and a second plurality of control zones corresponding to a second controllable subsystem;

generate, as the control signal, a first control signal to control the first controllable subsystem based on a first a control zone, of the first plurality of control zones, in the functional predictive control zone map and based on a geographic position of the agricultural work machine; and

generate a second control signal to control the second controllable subsystem based on a second control zone, of the second plurality of control zones, in the functional predictive control zone map and based on the geographic position of the agricultural work machine.

12. A computer implemented method of controlling an agricultural work machine comprising;

obtaining an information map that includes values of a first agricultural characteristic; corresponding to a set of geographic locations in a field, wherein the first agricultural characteristic comprises cut height or cut height variability;

detecting, with an in-situ sensor, a value of a second agricultural characteristic, different than the first agricultural characteristic, corresponding to a first geographic location of the set of geographic locations in the field;

generating a predictive model that models a relationship between values of the first characteristic and values of the second characteristic based, at least, on a value of the first agricultural characteristic, in the information map, corresponding to the first location and the detected value of the second agricultural characteristic corresponding to the first location;

mapping a predictive value of the second agricultural characteristic at a second location of the set of locations in the field based on a value of the first agricultural characteristic, in the map, corresponding to the second location and the model; and

controlling a controllable subsystem based on the mapped predictive value of the second agricultural characteristic corresponding to the second geographic location.

13. The computer implemented method of claim 12, wherein detecting, with the in-situ sensor, the value of the second agricultural characteristic comprises:

detecting, with the in-situ sensor, as the value of the second agricultural characteristic, an operator command indicative of a commanded action of the agricultural work machine corresponding to the first geographic location.

14. The computer implemented method of claim 13, further comprising:

generating a functional predictive operator command map that maps, as the predictive value of the second agricultural characteristic, a predictive operator command value to the second geographic location in the field.

15. The computer implemented method of claim 14, wherein controlling the controllable subsystem comprises:

generating an operator command control signal indicative of an operator command based on the functional predictive operator command map; and

controlling the controllable subsystem based on the operator command control signal to execute the operator command.

16. The computer implemented method of claim 12, wherein controlling the controllable subsystem comprises:

controlling the controllable subsystem to adjust a setting of a header on the agricultural work machine.

17. An agricultural system comprising:

a communication system that receives an information map that includes, as values of a first agricultural characteristic corresponding to a set of geographic locations in a field, wherein the map is generated as an agricultural work machine performs a current operation in the field wherein first agricultural characteristic comprises one of cut height and cut height variability;

an in-situ sensor that detects a value of a second agricultural characteristic, different than the first agricultural characteristic, corresponding to a first geographic location of the set of geographic locations in the field;

a controllable subsystem;

one or more processors; and

memory storing instructions, executable by the one or more processors that, when executed by the one or more processors, cause the one or more processors to:

model, during the current operation, a relationship between the values of the first agricultural characteristic and values of the second agricultural characteristic based, at least, on a value of the first agricultural characteristic in the information map corresponding to the first geographic location and the detected value of the second agricultural characteristic corresponding to the first geographic location;

predict, during the current operation and prior to the agricultural work machine operating at a second geographic location during the current operation, a value of the second agricultural characteristic at a second geographic location of the set of geographic locations in the field based on a value of the first agricultural characteristic in the information map, corresponding to the second geographic location, and the modeled relationship; and

control the controllable subsystem, as the agricultural work machine performs the current operation in the field, based on the predicted value.

18. The agricultural system of claim 17, wherein the memory storing instructions, when executed by the one or more processors, further cause the one or more processors to control the controllable subsystem to adjust a setting of a header on the agricultural work machine based on the predictive value of the second agricultural characteristic in the functional predictive agricultural map.

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